Department of Social Policy
PhD in Demography/Population Studies

Essays on adolescents' time allocation and development

Grace Chang

London, February 2024

Grace Chang ORCID 0000-0002-9726-6379. This thesis is re-submitted in part fulfillment of the requirements for the degree of Doctor of Demography/Population Studies London School of Economics and Political Science. My thesis is supervised by Berkay Özcan and Stephen Jenkins.

Declaration of Authorship

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I consider the work submitted to be a complete thesis fit for examination. The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgement is made. In accordance with the Regulations, I have deposited an electronic copy of it in LSE Theses Online held by the British Library of Political and Economic Science and have granted permission for my thesis to be made available for public reference. Otherwise, this thesis may not be reproduced without my prior written consent.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 56, 212 words.

Declaration of funding and support

This thesis is funded by the LSE Departmental Scholarship Fund. The thesis is based on data that are available to registered users via the UK Data Archive website.

Grace Chang Zhi Ching

London, February 2024

Acknowledgements

I am humbled by the enormous amount of help I have received throughout my PhD. I cannot fully thank every person in detail who have supported me, and can only name a few here in this acknowledgements section.

I thank my dearest partner, Teig Parsons, for his enduring and patient love. Teig has also been a strong proponent of my research and my ability when I lost faith. A huge thanks to my parents, Veena and Chang, my two sisters, Esadora and Melanie, and my new family, for their ever continuing love and belief in me. My heartfelt thanks to all my friends who have been incredible cheerleaders, always inspiring me to do better. A special thanks to the 'Cool Peeps' gang who gave me solid advice about the PhD, shared PhD experiences, and just for their strong friendship since 2013.

I give special thanks my two supervisors, Berkay Özcan and Stephen Jenkins, whom I literally could not have done this thesis without. I have learnt an enormous amount from both supervisors. They have provided emotional, professional, and academic support throughout my PhD. They have tirelessly read and re-read my work, and miraculously have not grown tired of me yet. They are both incredible role models, and I will continue passing on the advice they imparted to me. I thank the examiners for their time and extensive feedback to improve this thesis. I am grateful to have met all my PhD colleagues at the LSE, who really are now my friends. They are all kind, warm, and highly intelligent peers who helped challenge and support me with my research ideas.

A big thanks to all the academic and administrative staff at the Social Policy Department for their work to create an efficient and collegial workplace. I thank my colleagues and friends at Young Lives who gave valuable academic feedback and career support. I am grateful to all conference attendees who paid special attention to my work and connected with me professionally. I thank the examiners for reviewing my work.

I could not have completed this thesis without all this support. Words cannot express how grateful I am for being surrounded by a strong community of amazing people.

Abstract

This thesis examines which kinds of activities foster or hinder adolescents' socio-emotional skills and mental wellbeing across three chapters.

First, I examine how adolescents' time allocation is associated with their self-esteem and self-efficacy at age 15, building upon research by Borga 2019 and Keane, Krutikova, and Neal 2020, also using longitudinal data for Ethiopia, India, Peru, and Vietnam. I estimate these relationships controlling for prior non-cognitive skills and background characteristics. I find that an additional hour of domestic work instead of education-related activities is associated with lower self-efficacy, significant for all countries except Peru. Work is more harmful for girls than boys, especially in India and Vietnam. More time in work instead of education-related activities is associated with lower skills, but not if adolescents spend more time in work instead of leisure.

Second, I examine whether students can develop life skills through paid work. Using longitudinal data on a cohort of English students, I model the development of university students' internal locus of control – the belief in one's ability to have control over their life events – at age 20/21. I find that engagement in paid work, but not hours spent in work, is associated with greater students' internal locus of control.

Third, I examine if more screen time is bad for adolescent mental wellbeing, distinguishing the types of screen activities and wellbeing measures. Using time diaries of 14-year-olds, I examine this relationship by gender and parental education, controlling for adolescents' prior mental wellbeing and background characteristics. Spending more time on social screen activities and internet browsing are more adversely associated with self-reported mental wellbeing, compared to playing e-games and passive video viewing. Girls are more vulnerable to the harmful associations of social screen time than boys, and parental education is not a protective factor for girls.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

While many studies acknowledge the importance of the adolescent period for developmental outcomes, few studies take a more comprehensive view of adolescents' time use, namely the full set of activities adolescents partake in, and the relationship to their developmental outcomes. Focus in previous academic work has often been on a specific activity, and its association with adolescent's development, which too have mainly focused on education-related outcomes. This focus on education-related outcomes overlooks other important domains of adolescent development such as mental wellbeing (Nature 2021; UNICEF 2021b). This thesis bridges this gap by examining the associations between adolescents' time use and their socio-emotional competencies and mental wellbeing. I present three papers around this key question: what kinds of activities foster adolescents' socio-emotional competencies and mental wellbeing?

I demonstrate in my first paper (Chapter 2) that, in developing countries, engaging in market work can bring a double disadvantage to adolescents' acquisition of socio-emotional competencies. In my second chapter (Chapter 3), I show that UK university students' engagement in paid work during their studies is associated with improved socio-emotional competencies compared to students who do not work. In my third paper (Chapter 4), I show for UK 14-year-olds that spending more time on screens is associated with lower mental wellbeing, but the associations differ depending on how screen time is measured, how well-being is measured, and the subgroups of adolescents analysed. In all three studies, I show that spending more time in leisure is not associated with improved or worsened adolescent mental wellbeing or socio-emotional competencies development. This thesis also argues that how individuals spend their time should be examine in detail, not only considering activities important for adolescent outcomes, but also the full range of activities in individuals' time budgets.

1.1 Conceptualisation of time as an investment and reflections of power

In modern society today, clock and calendar time are a standardised and quantifiable construct that people use to plan and allocate activities, and record events, throughout our life. The time when an event occurs such as when a child is born, or when an individual has passed, is recorded to the precision of hours, minutes, and seconds. We know that a day consists of 24 hours, a month has 30 or 31 days, and so on. With time as a quantifiable construct, researchers have been able to analyse social phenomenon that are not readily observed by the researcher.

In sociology, the most longstanding and well-established examinations of time use are known as time-budget studies (Adam 1994) which were investigations into people's use of time in their daily lives. Time-budget studies were initially not concerned with content but only with studying how much time was allocated for the family, work, and leisure. This information was, and still is, used as an indicator of particular lifestyles and the quality of people's lives: quality being measured by the amount of free time available (Staikov 1982).

In the majority of surveys, time allocation at the extensive margins (engagement in the activity) and intensive margins (hours spent) are usually measured retrospectively. While it is the simplest way to capture information, the types of activities asked about in the survey are determined by the survey team (e.g., whether or not to include questions about leisure time), and can be subject to recall bias and social desirability bias. Recall bias can occur because respondents typically are not skilled at perceiving time they spend engaging in specific activities (Grondin 2010), and can report their time spent inaccurately. Time diaries can help address these problems. Time use diaries collect a greater number of activities and improve upon the recall bias problem as the individual responds in within a shorter period – usually 10-minute windows or within 24 hours – compared to traditional surveys which can require individuals to recall activities and their duration that occurred up to a week, a month or a year. An additional benefit to time diary information is that the overall pattern of time use can be observed in a 24-hour cycle, and can be linked with other important information such as the levels of enjoyment related to the activity, and whether the activity was done alone or with others (co-presence). It allows the researcher to examine not only the activity of interest, but the activities substituted in place of the activity of interest, as well as provide some greater contexts to the situation when the activity was performed.

Practically, time use is a useful concept to reflect activities often performed by individuals observed by the researcher, such as economic work, but also activities that were “hidden” from the researcher often because it takes place within households. Time-diary studies historically focused on describing social conditions, monitoring economic productivity and providing labour force information. With the advent of technological advancements and social practices across time, time-use diary studies have played key roles in eliciting information about new behavioural patterns such as US households experiencing unexpected increases in unpaid domestic work time as a consequence of so-called ‘labour saving’ devices in the mid-twentieth Century (see Bauman, Bittman, and Gershuny (2019) for a short history of time use research). Time measures the amount that people allocate to activities, and constraints on people’s time can result from excessive or competing demands (e.g., Spinney and Millward (2010)) or from priorities e.g., when people have enough hours but the problem is how they allocate them (e.g., Trost et al. (2002)).

Theoretically, time use or time-budget studies are helpful in understanding processes of human behaviour, and if we want to investigate how identities are formed and reworked across time (Adam 1994). Time use is a helpful concept in reflecting investments or decision-making in which activities individuals decide to do (or not do), which are influenced by a variety of factors. It also has reflections about routine and control over one’s time. Within a zero-sum framework that treats time as a limited resource, there is only so much that can be done in one working day, and the remaining tasks need to wait. For example, take children at school. How school activities are allocated, prioritized and chosen on a zero-sum calculation of time resources of teachers and their students, on top of being coordinated into the structure of the school, the education system, and the socio-political system of the country as a whole (Ball 1984). People at home are influenced in their timing by their own habits, as well as of the people around them. They cannot separate themselves from the institutional timetables imposed on other members of their family.

Once we ask who structures whose life, what rules are being adhered to, and how these processes occur, then timed social life becomes fundamentally embedded in the understanding of the structural relations of power, normative structures, and the negotiated interactions of social life. Time is not created equally, and is a part of conceptual power. Who has the luxury to allow other activities "to wait", if time is treated as a limited resource? Activities that "can wait" becomes intricately linked with social status and power dynamics, and can be understood as an expression of unequal social relations. Similarly, who is able to optimise the level of activities within the limited resource (e.g., by paying a third party to do certain activities)? We can see this from the "work-life balance" literature (the opposite coin of work-life conflict), which typically is used to explain the dilemma or possibility in balancing the two so-called separate spheres of 'work' and 'life' domains for working adults. If the balancing of these spheres fail, then it becomes an issue of work-life conflict. Evidently, the (in)ability to manage time is strongly tied with advantage, which I will discuss later in this chapter, that gender and socio-economic background play a strong role in from a very early age.

For the purpose of my investigation, where I am marrying time use and skills development, this thesis focuses on how time reflects investments, which is a useful way to conceptualise time because it reflects the ability or possibility for adolescents autonomy over themselves, which shapes their identity. The concepts of time I will use are both based on retrospective information and time diaries, but where possible, I use time diaries as they are superior in being able to show the full time budget (what is done, and not done) and provides granular detail in the types of activities performed.

1.2 Time investments during the adolescent period

The period of adolescence is important for life outcomes for several reasons. It is a time of neural development and emotional learning where adolescents learn how to conceptualise their identities in adult social contexts (Andersen and Teicher 2006; Dahl et al. 2018). It is a time where they may experience key demographic changes such as completing full-time education, entering the labour market, and/or family formation (Schoon and Lyons-Amos 2016). Adolescents are also the first adopters of new trends and devices such as new technology (Dahl et al. 2018).

In the past, adolescence referred to the period of transition from childhood to adulthood, starting at the beginning of puberty and ending with family formation (Feldman and Elliott 1990). Today, the endpoints are less clear as the ages at which young people adopt 'adult responsibilities' such as family formation and financial independence vary across the world, and relates to as late as 24 years old. In developed countries, there are trends which show postponement in transitions to adulthood, while in developing countries there are typically early years of adulthood adoption, especially in a low-resource setting. With global nutrition and health improving too, adolescent's age of puberty has fallen, thus reducing the lowest age band to 10. Since I am interested in a wide range of activities adolescents do which may reflect their decision-making, such as engaging in paid work which happens at younger ages in developing countries but older ages in developed countries, I examine this wide range of the adolescent period. Thus, I follow the Lancet Commission by Patton et al. (2016) and the Partnership for Maternal, Newborn and Child Health (PMNCH) in referring to the ages between 10 and 24 years (inclusive) as adolescence. In this thesis, Chapters 2-4 will examine different age groups of adolescents within this age window.

The adolescent period, spanning ages 10 to 24, is notably marked as a sensitive phase for social interaction. Adolescents exhibit heightened sensitivity to social stimuli and the adverse impacts of social exclusion. In contrast to children under 10, adolescents allocate more time to peer relationships than to family connections, forming intricate peer associations. Peer social approval gains increased significance during adolescence, influencing young individuals more profoundly. Adolescents demonstrate a heightened sensitivity to peer acceptance, rejection, and approval compared to both children and adults. This shift toward peer relationships aids in the development of independent adulthood, fostering a more comprehensive social self-identity and strengthening bonds within the peer group. Concurrently, cognitive abilities such as self-referential processing, executive control, and mental development improve throughout adolescence, enhancing young individuals' capacity to understand others' perspectives. The development of advanced cognitive processes equips adolescents with the mental tools to introspect and navigate social networks that initially emerge as unstable and less reciprocal but gradually evolve into more refined and reciprocal structures throughout adolescence. Exploring these age brackets is of interest to understand how semi-autonomous adolescents acquire competencies and are influenced in their mental well-being.

In adolescent research, a prevalent perspective posits certain behaviors as desirable (e.g., long-term planning) and others as undesirable (e.g., risk-taking). While long-term planning can contribute to achieving high-quality and stable adult lives for many individuals, external factors may hinder this goal despite their use of such planning (Ellis et al. 2012). In specific situations, taking risks might increase the likelihood of attaining the desired outcome. The highlighted research underscores the influence of contextual cues on adolescent behaviors. Shifting from isolating adolescent behaviors, especially risk-taking, to a model that integrates social environmental cues could enhance our understanding of these behaviors and improve interventions. What is often perceived as issues with adolescents—such as risk-taking, poor impulse control, and self-consciousness—actually reflects brain changes that present excellent opportunities for education and social development.

Adolescence provides a window of opportunity for acquiring new skills and shaping an adult identity. Studies on brain development suggest that adolescence might be a period of heightened neural plasticity, particularly in brain regions related to executive function and social cognition. The exploration of the brain's role in adolescent social development could guide decisions on "when to teach what," informing curriculum design and teaching practices to capitalize on periods of neural plasticity for optimal learning.I am interested in these age bands because I am interested in how (semi-autonomous) adolescents may learn competencies, or are influenced in their mental wellbeing.

Health and social policies for adolescents, until almost a decade ago, were largely neglected until recently because policy practitioners assumed that adolescents were at the peak of their health (Patton et al. 2016). Currie (2020) argues that economists have undertaken little research about teenagers because they have focused on ‘risky behaviours’ during teenagehood, and believed that investments or interventions earlier in childhood are more effective than later in life. In more recent years, there has been growing recognition by global institutions that investments during this period are critical to bring a ‘triple dividend of benefits’, that is, benefits for the current adolescent population, benefits for their future adult outcomes, and for future generations to come (WHO 2020, 2017; Sheehan et al. 2017; Patton et al. 2016). For 75 low income, lower-middle income, and upper-middle income countries, Sheehan et al. (2017) estimated that an investment of USD 5.2 per capita each year to improve adolescents’ physical, mental, sexual, and reproductive health would bring economic and social benefits of ten times their costs by saving 12.5 million lives, preventing more than 30 million unwanted pregnancies, and averting disability. Adolescence has been made an integral part of The United Nations Global Strategy for Women’s, Children’s, and Adolescents’ Health (2016-2030) and the 2030 Agenda for Sustainable Development in order to fulfil goals such as gender equality, health improvement, poverty alleviation, and economic growth (WHO 2014).

During childhood, parental time investments such as playing with or reading to their child, play a large role in childhood development (Meroni, Piazzalunga, and Pronzato 2021; Hernández-Alava and Popli 2017; Del Bono et al. 2016; Fiorini and Keane 2014; Hsin and Felfe 2014; Todd and Wolpin 2007; Cunha et al. 2006). As children become adolescents, there is diminishing positive marginal effects of parental investments on their children’s development (Del Boca, Monfardini, and Nicoletti 2017; Cunha and Heckman 2008). This suggests that adolescents start gaining some autonomy over their own actions, and their skills acquisition and learning begin to depend on their own time investments, such as how much time they spend on home work or playing games. For example, Del Boca, Monfardini, and Nicoletti (2017) showed that US mothers’ investments are important for their children’s cognitive test scores at ages 6 to 10, but not during adolescence (ages 11 to 15). The authors also demonstrate that adolescents' own time investments affect their cognitive outcomes in adolescence, but not during childhood.

The 21st century has brought changes in how adolescents spend their time. For example, Crosnoe and Johnson (2011) argue that US adolescents, at the start of the 21st century, have smaller family sizes and increased participation in school and paid work than earlier cohorts, and use new media and technologies. Mullan (2018) compared the time use patterns of UK adolescents aged 8–18 years in 2000 and in 2015. He showed that adolescents in 2015 led more home-based, sedentary lifestyles, and spent more time on screen-based activities. The advent of technological integration into everyday life has meant that activities and tasks occur faster, with less 'waiting' time; people rush through tasks or do tasks simultaneously (Southerton 2003). However, most of the evidence about how technology and the premium placed on efficiency and speed on how people divide their time is mostly focused on working adults. These changes highlight the importance of examining across a wide range of activities, for adolescents in the 21st century. How young people spend their time are determined by their environment, family, and resources. For adolescents, technology has allowed a new means of socializing, managing workload and performance, which differs at different points in their life.

This also has inequality implications. Typically, compared to their more advantaged peers, disadvantaged adolescents not only spend less time in education-related activities, they spend more time in work, and spend their leisure time differently. If less advantaged adolescents are less able to invest time in activities that improve their test scores, then how is the time spent in these so-called "other" activities associated with their development? The focus on activities only relevant to academic achievement misses out potential benefits or double disadvantages to their development.

1.3 Adolescent wellbeing

Thus far we have discussed how adolescent time use is based on the framework that time reflects adolescent agency, as well as parental influence (e.g., having resources to be able to make that choice) about their investments onto themselves. With that, we also need to ask ourselves about the end or outcomes these investments aim to achieve. Thus, we need to define what success in adolescent development means. In quantitative studies of adolescent behaviours, too often previous literature on favourable adolescent achievements focus on academic achievement, labour market outcomes, or delinquent behaviour. While cognitive scores are important measures of human capital, they are not the only measure.

Heckman and Kautz (2013) demonstrate that achievement test scores at adolescence only explain at most 17% of the variability in future earnings. They argue that success in life depends on many traits, mainly championing personality traits or socio-emotional skills. This lacks a comprehensive examination of what it means to achieve a good life. Conceptualizing success in this broader way may move us forward by aligning more closely with the more holistic set of goals we have for our children and youth, but this broader definition poses a host of challenges. We arrive at a much more ambiguous definition of success that does not lend itself to being easily measured. As a step towards contributing to our understanding and measurement of a more 'holistic' measure of wellbeing, this thesis attempts to draw a framework with a special focus on outcomes less examined for adolescents.

1.3.1 Socio-emotional competencies

There is a growing scientific literature across fields of psychology, economics, sociology, and education demonstrating that success in life is influenced not only by intelligence and opportunity, but also by people's capacities to maintain social relationships, regulate emotions, and manage goal and learning-directed behaviours – personal qualities that can be distinguished from cognitive ability as measured by intelligence tests (Duckworth and Yaeger 2015).

The rapid growth in interest and study of these capacities however, have left the literature with a variety of terminologies to describe similar concepts, such as socio-emotional skills, personality traits, social and emotional skills, soft skills (Abrahams et al. 2019; Duckworth and Yaeger 2015). Some economists and psychologists propose that personality traits are indeed skills (Kautz et al. 2014), but others have distinguished skills from traits (Duckworth and Yaeger 2015). While skills and personality are related, the literature that distinguishes between the two argue that social and emotional skills pertain to an individual's ability to manage emotions, communicate effectively, and navigate social relationships. These skills are dynamic and can be developed over time. In contrast, personality refers to an individual's enduring and relatively stable traits and tendencies that influence how they think, feel, and behave.

In this thesis, I am interested in how time use is associated with the development of these capacities, which implies learning. OECD (2021) defines socio-emotional skills as

> "A subset of an individual's abilities, attributes and characteristics that are important for individual success and social functioning. They encompass behavioral dispositions, internal states, approaches to tasks, and management and control of behavior and feelings. Beliefs about the self and the world that characterize an individual's relationships to others are also components of social and emotional skills."

In line with Soto, Napolitano, and Roberts (2021) and Schoon (2021) who have proposed taxonomies to more concretely conceptualise such skills, I use the terminology socio-emotional competencies. I acknowledge that while personality and skills may reciprocally influence each other (Casillas, Way, and Burrus 2015; Dweck 2017), my thesis focuses on examining the development of learnable skills through various activities, across the life cycle. I combine both taxonomies proposed in Schoon (2021) and Soto, Napolitano, and Roberts (2021) in Table 1.1 below, which maps onto other already established frameworks.

Table 1.1: Author’s compilation of taxonomies of socio-emotional competencies by Schoon (2021) and Soto et al. (2021)

Basic psychological needs (SDT)	Schoon (2021) Domains/manifestations		Soto et al. (2021) Skill domain: definition	Big Five	CASEL	Examples
Autonomy	Self-orientation	Affect Cognition	Emotional resilience: Capacities used to regulate emotions and moods	(Low) neuroticism	Self-awareness	Happiness Self-efficacy Confidence regulation
		Behaviour	Self-management: Capacities used to effectively pursue goals and complete tasks	Conscientiousness	Self-management	Self-control Emotion regulation Independence
Relatedness	Other-orientation	Affect Cognition	Social engagement: Capacities used to actively engage with other people	Extraversion Agreeableness	Social awareness	Compassion Trust Persuasive skill
		Behaviour	Cooperation: Capacities used to maintain positive social relationships		Relationship skills	Pro-social behaviour Connection
Competence	Task-orientation	Affect Cognition Behaviour	Innovation: Capacities used to engage with novel ideas and experiences	Openness to experience	Responsible decision making	Passion Optimism Persistence/effort Creative skill

In Schoon's domains (DO) and manifestations (MA) of socio-emotional competencies (SEC), from hereon called DOMASEC, she distinguishes between intrapersonal, interpersonal, and task-oriented competencies, which are manifested in associated feelings, cognitions, and behaviours. She maps these domains/manifestations onto basic psychological needs based on self-determination theory (SDT) (Ryan and Deci 2017) which specifies that fulfilling a set of universal basic psychological needs (autonomy, relatedness, and competence) is essential for psychological growth and effective functioning. Autonomy encompasses the ability to regulate one's emotions and actions, enabling individuals to make self-directed choices. Relatedness involves valuing and receiving care from others, while competence entails actively contributing to a purpose, feeling challenged, and achieving effectiveness (Ryan and Deci 2017). The link between SDT and the domains/manifestations then centers on the idea that individuals play an active role in their own development, highlighting that socio-emotional competencies evolve over time through interactions with others and within various contextual influences.

In Soto, Napolitano, and Roberts (2021), they proposed five major domains for what they term social, emotional and behavioural skills that correspond within the Big Five traits. In both Soto, Napolitano, and Roberts (2021) and Schoon (2021), each domain is a set of functionally related capacities instead of consistent tendencies across the same situations, and both map onto the Big Five, with Schoon (2021) also mapping onto CASEL constructs, as shown in Table 1.1. Soto, Napolitano, and Roberts (2021) acknowledges that some skills blend aspects of multiple domains.

In this thesis, I pay special focus to competencies that may be most relevant for the adolescent period for reasons described in the previous sub-section, that the adolescent period comprises of several stages of self-concept, self-image, self-awareness, especially in comparison to their family, peers, and their environment. Therefore, it mainly focuses on how adolescents' activities are related to self-orientation (which includes both emotional resilience and self-management), as well as other-orientation (mainly on social engagement), on socio-emotional competencies such as self-esteem, self-efficacy, and locus of control.

Examining socio-emotional competencies during adolescence is relevant because studies show that these competencies are learnable, continue to develop after childhood, and are more sensitive to investments than cognitive skills (Borghans et al. 2008; Cunha and Heckman 2008). Soto, Napolitano, and Roberts (2021) posit that socio-emotional competencies are moderately stable over time but most competencies gradually increase with age because of accumulated knowledge and practice in relevant contexts (e.g., self-management skills at school and work). Elkins, Kassenboehmer, and Schurer (2017) investigate the stability of the Big-Five and locus of control over an eight-year time frame in adolescence and young adulthood using nationally representative panel data from Australia. They show that most of these competencies change between adolescence and young adulthood. Arsandaux et al. (2023) also find that self-esteem is affected by childhood and adolescent factors, up until college-years, with freshmen being the most vulnerable, as transitions to college represent either a period of challenges in terms of behavioural, physical, and mental change, or an opportunity to live an independent life with new social roles (Harter 2006).

There is a growing literature in developed countries, mainly in the USA and Europe, that demonstrates that having greater socio-emotional competencies is strongly associated with better adult social behaviour, education and labour market outcomes (Heckman, Jagelka, and Kautz 2021; Almlund et al. 2011; Heckman, Stixrud, and Urzua 2006). Studies such as by Roberts et al. (2008) and Heckman and Kautz (2013) have also provided evidence that the Big Five measures and internalising and externalising behaviour predict later labour market outcomes, mortality, and divorce, as strongly as cognitive ability. While less evidence is available about developing countries, some research show positive returns to having more socio-emotional competencies. For example, Cunningham, Torrado, and Sarzosa (2016) found that cognitive skills (verbal tests, numeracy) and socio-emotional competencies (Big Five, grit) are positively correlated with earnings and labour market outcomes in Peru. Campos-Vazquez (2018) found returns on monthly earnings in Mexico for both cognitive skills and locus of control, even after controlling for family background and educational attainment but with gender gaps in skills returns. In sum, there is growing interest in the importance of these skills, and there is room for research about how these skills are formed, especially in developing countries.

There is extant research about the effects of parental time inputs on the formation of children's socio-emotional competencies primarily in the USA, Europe, and Australia (Meroni, Piazzalunga, and Pronzato 2021; Hernández-Alava and Popli 2017; Del Bono et al. 2016; Fiorini and Keane 2014; Hsin and Felfe 2014; Cunha et al. 2006) and a few developing countries such as Colombia (Attanasio et al. 2020). However, there are limited studies about adolescent time allocation, and its relationship to adolescents' socio-emotional skills formation, except for a handful of studies (Nguyen et al. 2022; Jürges and Khanam 2021; Borga 2019; Del Boca, Monfardini, and Nicoletti 2017). This leaves an evidence gap, which I address in my thesis.

While I have highlighted the importance of socio-emotional competencies, they are also inherently linked to adolescent mental wellbeing, a concept which has recently been gaining attention, especially since global lockdowns during Covid-19. The taxonomy described in Table 1.1 above which integrates several personality models and the SDT helps us conceptualise how personality development, motivation, competencies, and wellbeing are all interlinked (Ryan, Soenens, and Vansteenkiste 2019).

1.3.2 Mental wellbeing

According to UNICEF (2021b), more than 13 per cent of the world's adolescents, aged 10 to 19, globally lived with a mental disorder in 2019. In a 2021 Gallup survey for UNICEF across 21 countries, one in five 15- to 24-year-olds reported that they often felt depressed or had little interest in doing things (UNICEF 2021a). Nature (2021) highlighted how these reports in 2021 were the first time that UNICEF had discussed challenges and opportunities for preventing and treating mental-health problems in adolescents, demonstrating how adolescent mental health issues have been understudied and underfunded. Neglecting adolescents' mental wellbeing issues can bring large financial and social costs to society, such as mortality from suicides and violence, as well as losses in potential human capital (UNICEF 2021b).

My research contributes empirical findings about adolescents' mental wellbeing. I use the term mental wellbeing because I am interested in the broad concept of emotional, psychological and social wellbeing, and this is closely associated with socio-emotional competencies (Lucas and Diener 2009; Huppert 2009; Ross et al. 2020). Mental wellbeing indicators are interesting because they provide evidence about a so-called 'flourishing' life or 'positive mental wellbeing', terms coined by Huppert (2009) to describe high levels of mental wellbeing. She argues that positive mental wellbeing should be examined not as merely an absence of mental health disorders, but rather in its own right. She also argues that examining flourishing lives can help enhance our understanding of the wellbeing of the majority who do not have mental illness.

Within the definitions of wellbeing, one can distinguish between hedonic and eudemonic approaches (Deci and Ryan 2008). Hedonic wellbeing is happiness or the experience of positive affect instead of negative affect. Studies often cite the use of subjective wellbeing when measuring hedonic wellbeing. Eudemonic wellbeing focuses on the meaning of life, and living life in a deeply satisfying way, such as by having autonomy, self-determination, and psychological wellbeing. Despite there being two distinct ways of measuring wellbeing, scholars have argued that wellbeing is best conceived in a multidimensional way which includes both definitions (Proctor, Tweed, and Morris 2015; Biswas-Diener, Kashdan, and King 2009).

In my research, I examine both the hedonic and eudemonic elements of mental wellbeing. To measure *adolescents'* life satisfaction, I use Huebner's Multi-Dimensional Student Life Satisfaction Scale (Huebner, 1994) which is a widely used measure of adolescents' wellbeing in five domains: family, friends, school, living environment, and self. Zǔkauskiene (2014) highlights relationships with parents, nonparental adults, and peers, as important domains for adolescents' psychological and mental well-being. Having good relationships with parents enable adolescents to feel purposeful and capable of coping with future events, which can usually be measured by greater self-esteem and agency, measures that overlap with measures of socio-emotional competencies. Note that these measures also overlap with measures of socio-emotional competencies. Note that these measures also overlap with measures of socio-emotional competencies. Nonparental adults such as teachers, relatives, and other community members can help support adolescents in ways that parents cannot, especially for adolescents from less advantaged backgrounds, such as by providing higher levels of positive academic attitudes or support if parents divorce. Finally, Zŭkauskiene (2014) argues that peers play an important role in feelings of inclusion, self-worth, and belonging. High levels of mental wellbeing are not only related to individuals feeling good, but have also been shown to be associated with effective learning, productivity, and good health and life expectancy (Neve et al. 2013; Diener and Chan 2011; Dolan, Peasgood, and White 2008).

In their operationalization of 'flourishing' wellbeing, Huppert and So (2013) identified two main factors from the ten flourishing indicators they designed for the European Social Survey (Huppert et al. 2008) The first factor comprised of 'positive characteristics', which were emotional stability, vitality, optimism, resilience, positive emotion, and self-esteem. The second factor 'positive functioning' comprised of engagement, competence, meaning, and positive relationships. In the present thesis, each chapter uses a measure of either 'positive characteristics' or 'positive functioning'. Chapter 2 reflects each factor using self-esteem and self-efficacy respectively. Chapter 3 only examines locus of control which only reflects 'positive functioning'. Chapter 4 also examines both positive characteristics (self-esteem, happiness with how they look, happiness with life), and positive functioning (happiness with friends, family, school, school work). It also examines reported emotional and behavioural scores by the parents (Strengths and Difficulties Questionnaire) which is commonly used to screen for mental health disorders in adolescents, while may be the opposite measure to 'flourishing' wellbeing, provides measures od the adolescent's 'positive characteristics'. These measures reflect the concept of flourishing because it relates to the presence of happiness, having a purpose and sense of meaning, and good relationships (VanderWeele, McNeely, and Koh 2019).

1.3.3 Adolescent wellbeing framework

There is a general agreement that adolescent wellbeing is multidimensional, often encompassing both objective and subjective measures. According to Diener et al. (2009), objective definitions of wellbeing are ideal views that are independent of an individual's own subjective values and norms, such as physical health. Subjective definitions are perceptions or preferences in reference to an individual's own interest, needs, or desires. For example, an individual is living a good life only if the individual evaluates their life positively. Using an example by Diener et al. (2009), these two definitions may be aligned. For example, having good physical health is objectively good, and having good health is also likely to play an important role in subjective wellbeing as individuals prefer to be healthy.

Objective indicators of wellbeing such as school attendance and physical health are usually more readily measured than subjective wellbeing indicators such as happiness. They are typically incorporated into macro-indicators to measure how well a country or its population is doing, such as the Multidimensional Poverty Index which includes indicators such as nutrition and years of schooling. On the other hand, subjective measures of wellbeing are less readily measured or understood because they are perceived to be more 'fuzzy' measures that rely on self-reports of individual wellbeing. Several studies have shown that subjective measures of wellbeing are valid and correlated with biological processes and improved health and behavioural outcomes (Krueger and Stone 2014; Neve et al. 2013). Subjective measures can provide useful additional information over and above objective measures regarding the quality of people's lives, such as factoring in peer support in childhood obesity programmes in line with objective health measures (Hicks, Tinkler, and Allin 2013).

Research about factors that shape adolescents' subjective wellbeing such as mental wellbeing and socio-emotional competencies is in its infancy. An editorial in Nature, which refers to a UNICEF (2021b) report, highlights how the mental wellbeing and mental health issues of adolescents have largely been neglected until recently (Nature 2021). The UNICEF (2021b) report discusses how research about adolescents' wellbeing remains fragmented and mainly focuses on adults, not adolescents, despite adolescence being the peak period for the onset of most mental health conditions. Currie (2020) also argues that teenagers' mental health is overlooked in research by economists. While organisations such as the WHO (2020) and UNICEF (2021b) argue for a shift in the narrative about adolescents from "surviving" to "thriving" by promoting mental health, there remains a lack of research about adolescents' mental wellbeing.

There have been efforts to create a framework for adolescent wellbeing. The UN H6+

Technical Working Group on Adolescent Health and Well-being developed an expanded definition of adolescent wellbeing (Ross et al. 2020).[1] As seen in Table 1.2 below, the definition includes five domains of wellbeing for 10- to 19-year-olds: (Domain 1) good health and optimum nutrition; (Domain 2) connectedness, positive values, and contribution to society; (Domain 3) safety and a supportive environment; (Domain 4) learning competence, education, skills, and employability; and (Domain 5) agency and resilience. This framework has also been used by PMNCH which partnered with UN H6+ Technical Working Group for adolescents aged 10 to 24 years old, and expanded upon by institutions such as Gender and Adolescents: Global Evidence (GAGE) to apply to the study of adolescents in low and middle-income countries (Gugliemi, Neumeister, and Jones 2021).

The framework provides a useful way to conceptualise domains of focus for adolescent wellbeing. Each of the domains listed in the framework has the "emotional" type of wellbeing as a common factor, which is the core outcome of analysis in this thesis, and there is an acknowledgement that these five domains are inter-linked; socio-emotional competencies (e.g., self-esteem and agency) is related with good mental and physical health (and I focus on mental wellbeing). Importantly, the framework also provides a list of subdomains and requirements as examples on how these adolescents may be able to achieve these domains of wellbeing. This is pertinent to the issue of time use, since I examine in some cases how a specific activity (e.g., paid work) may be related to the adolescent's ability to learn competencies (Domain 4) as well as agency and resilience (Domain 5), but the relationships between time use and outcomes may be related to the requirements listed in Domain 2 regarding connectedness; that adolescents engaging in paid work may feel they are contributing more to their family and hence have greater self-esteem. This relationship can also be related to Domain 3 in that this relationship depends whether the activity pursued is done in a safe and supportive environment.

More specifically, I implement the UN definition of adolescent wellbeing in my research with a main focus on learning and competence, and agency and resilience in Chapters

[1] The UN H6+ Technical Working Group on Adolescent Health and Well-being includes representatives of PMNCH, UNAIDS, UNESCO, UNFPA, UNICEF, the UN Major Group for Children and Youth, UN Women, the World Bank, the World Food Programme and the WHO.

Table 1.2: Simplified version of adolescent wellbeing by Ross et al. (2020)

No.	Domain	Sub domains	Types of well-being
1	Good health and optimum nutrition	Physical health and capacities Mental health and capacities Optimal nutritional status and diet	Physical Nutritional Emotional Sociocultural
2	Connectedness, positive values and contribution to society	Connectedness Valued and respected by others and accepted as part of the community Attitudes Interpersonal skills Activity Change and development	Emotional Sociocultural
3	Safety and a supportive environment	Safety Material conditions Equity Equality Non-discrimination Privacy Responsive	Physical Emotional Sociocultural
4	Learning, competence, education, skills, and employability	Learning Education Resources, life skills, and competencies Skills Employability Confidence they can do things well	Emotional Cognitive
5	Agency and resilience	Agency Identity Purpose	Emotional Cognitive

2 and 3. In Chapter 4, I expand these measures to measure 'flourishing' wellbeing which encompasses all Domains.

1.4 Framing the relationships between adolescent time use and their socio-emotional competencies and wellbeing

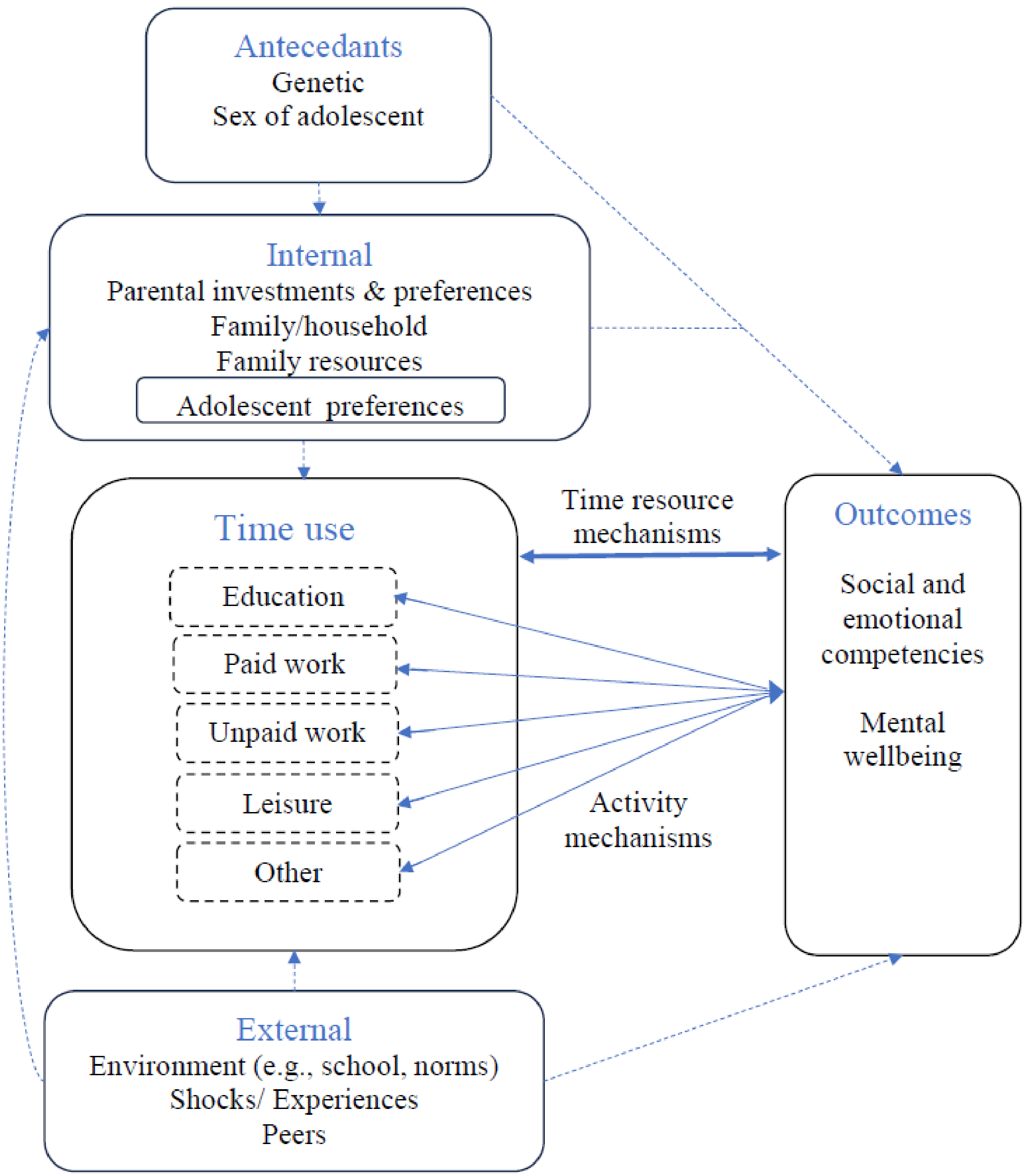
Despite growing evidence that investments during adolescence is a key stage for successful adult outcomes, there is little evidence about which activities are important for adolescents' socio-emotional competencies and mental wellbeing, and the pathways relating them. Academic research that examines adolescents' investments and their development often measures adolescents' success in terms of academic achievements (e.g., cognitive skills measured through test scores), and focuses on a single, usually retrospectively reported, activity that adolescents do to boost or harm these achievements (e.g., school attendance or a risky behaviour).

An activity which may be good for cognitive development e.g., homework, may not necessarily be good for mental wellbeing. For example, Caetano, Caetano, and Nielsen (2024) showed using time diaries of children and adolescents aged 5 – 18 that time spent in "enrichment activities" such as homework or reading, are close to zero for cognitive skills but have a negative association for behavioural competencies, especially for adolescents in high school. The authors find that youth spend so much time on homework that on average, the last hour spent on these activities actively harm their behavioural competencies with no offset gain to their cognitive skills. Along with recent studies to date (Borga 2019; Jürges and Khanam 2021; Keane, Krutikova, and Neal 2020; Meroni, Piazzalunga, and Pronzato 2021), my thesis provides new evidence about the nature of this relationship and to do so, I frame these relationships in the conceptual framework below.

I propose a framework that combines theories from sociology, economics, and psychology, to explain the potential relationships between adolescent time use and their socio-emotional competencies and mental wellbeing, where the use of each theory previously only helped explain a sub-set of potential relationships. Consider Figure 1.1 below, where each 'box' groups a concept or a set of factors. Solid lines indicate the main relationships of analyses, and the dotted lines show the links between several factors of interest.

Let us take an adolescent at one time period, and in the third box from the top, their time use is made up of several types of activities, and here I list some examples such as time in education, paid work, unpaid work (e.g., house chores), leisure, and any other activities (e.g., idle time, illicit activities). All these activities are linked together to make up the adolescent's overall "time use". Distinguishing the difference between each of the activities and the adolescent's time use is important in unpacking these relationships with the outcomes of interest. Since I am interested in the adolescent period where social standing, self-image and self-concept during this time are particularly important, we should expect that each activity might influence adolescents' outcomes positively as a spillover from gaining certain capabilities or skills from the activity, or allowing the adolescent to have greater social standing or acceptance among peers (i.e., if the activity is seen as shameful or not). Let us first examine this in what I term "Activity mechanisms", where we discuss how each type of activity may influence adolescents' socio-emotional competencies and mental wellbeing.

Figure 1.1: Author's proposed integrative conceptual framework



1.4.1 Activity mechanisms

Education

Engagement in each of these activities may directly bring about so-called “good” or “bad” learning. Drawing upon the human capital theory (Schultz 1961; Mincer 1974; Ben-Porath 1967; G. S. Becker 1964) which posits that time spent in a certain activity, and in most examples typically quote on-the-job training or schooling, allows the acquisition of knowledge and skills termed ‘human capital’. Studies have shown that time in educational activities such as attending school, and doing so-called “enrichment activities” such as doing homework, reading a book, are related to improved self-esteem and locus of control (Heckman, Pinto, and Savelyev 2013; Kautz et al. 2014)

Paid work

Fewer studies have paid attention to adolescent’s time spent in activities besides schooling, but there is evidence in adult populations that work experiences influences self-esteem (Krauss and Orth 2022) and locus of control (Gottshalk 2005), because being engaged in work is a form of social inclusion as an acceptable member of society, and certain types of work is associated with greater perceived social standing (Leary 2012). However for adolescents, and depending on the societal norms in the country of residence, engagement in paid work may be because of a cost-benefit decision (e.g., working during university to save for a holiday or to contribute to personal expenses), or a needs-basis (contribution to family income), indicated by the arrow from “Internal” factors to time use. The work experience itself may allow on-the-job learning (Arrow 1962), such as having more confidence in one’s ability to manage colleagues and clients. As a spillover or indirect effect, the ability to earn for themselves or their family may allow the adolescent to feel more autonomous about their life choices, in turn improving their self-esteem, self-efficacy, and mental wellbeing. This can be explained by the Expectancy Value Theory of Achievement (Wigfield and Eccles 2000), the adolescents’ performance on an activity can be explained by their beliefs about how well they will do on the activity, and how much they value the activity. Work mastery (or failure) may lead to adolescents developing more positive (or negative) socio-emotional development.

Unpaid work

Adolescents' unpaid work such as domestic chores and care work are activities rarely examined in quantitative studies, with more of this focus on adult women and families. There are also missing evidence depending on the country studied. For example, a systematic review about young carers (aged <18 years old) mainly in the UK, Europe, and North America show that young carers are more likely to have poorer physical and mental health, on average, than their non caregiving peers but evidence is relatively weak because most studies only examine one period of time, no studies were about low and middle-income countries, and there lacked an explanation for the mechanisms for this relationship (Lacey, Xue, and McMunn 2022). For domestic work, prevalence of these activities among adolescents in developed countries are documented, such as in Finland, Spain, and the UK (Gracia et al. 2022), but the majority of studies relating adolescents' domestic work and their outcomes tend to focus on developing countries, where the majority of evidence also points to poorer self-esteem, self-efficacy, and physical and mental wellbeing (Putnick and Bornstein 2015; ILO 2018a).

Note however, that the literature also describes how there may be a reverse relationship between said activities and adolescent's social and emotional development. For example, the meta-analysis by Krauss and Orth (2022) show that the relationship between work experience and self-esteem is bi-directional. I acknowledge this by showing that the arrows are double-headed in Figure 1.1 above. There will be a more extensive discussion about this in Section 1.7 "Estimation challenges and strategies" below.

Other

There are obviously many activities still not covered here but for completion sake, I include this so-called "Other" category which may encompass activities like commuting, sleeping, physical activities, illicit activities, and so on. The point of highlighting this category is that while each of these activities may have a direct relationship to adolescents' social and emotional development, many studies typically only examine one type of activity (e.g., schooling or smoking or paid work), which implicitly assumes that all the alternative activities may be bundled as one "Other" activity.

1.4.2 Time Resource Mechanisms

This brings us to discussing the inter-relationship between each individual activity, which is the adolescent's overall time use, which I term overall as the "Time Resource mechanisms". Given that there are limited hours in a day, increasing more time spent in one activity – even if not necessarily harmful – reduces time spent (or stops engagement) in the "Other" activity. There are several terms used for this phenomenon, such as time constraint, opportunity cost, displacement, and the "zero-sum theory", but in essence argues that time spent in one activity (if presumed bad), reduces time in other (presumed good) activities. For example, Burston (2017) found that since adolescents know the best bet they have for their future is through entering higher education but they are unable to afford it, they become time poor as they need to navigate the system of working and studying. Working itself may not be necessarily detrimental to academic performance (Nonis and Hudson 2006) but financial stress can have a negative effect on students' sense of efficacy, productivity and wellbeing (Robotham 2008; Melius 2010). For example, adolescents who spend more time in paid work may spend less time attending school compared to adolescents who do not work. In turn, adolescents who do paid work may feel ashamed for not being able to spend time with friends in school, or to be seen as poor and having to do paid work, signalled by their poorer school attendance, thereby lowering their self-esteem and happiness.

This is also in line with other concepts usually used to explain behaviours of working adults such as work-life conflict, which posits that there are two or more spheres or domains that are mutually incompatible and viewed as competing actors for an individual's time, energy and behaviour. Within this frame, the effects of navigating multiple activities are viewed to increased stress, anxiety, or depressive symptoms, with negative spillover effects on family and peer relationships (Kossek and Lee 2017). There may also be spillover effects in the day, where time spent in paid work may mean that the adolescents goes to bed at a later time than usual, and studies have shown that sleep deficiencies are associated with poorer mental health, worse behavioural problems and moods (Gilchrist et al. 2021; Short et al. 2020).

The "zero-sum theory" is commonly cited in most research about adolescent activities, but studies are often limited by using a single measure of an activity rather than the full set of activities done within the day, which makes it difficult for researchers to know which activities are actually being displaced (e.g., see Dickson et al. (2018) about this issue in relation to screen use, e.g., whether screen time displaces physical activity or more idle time). This is important to distinguish because the hypothesised displaced activity may not be as expected. Research by Keane, Krutikova, and Neal (2020) and Jürges and Khanam (2021) demonstrate how considering the full time budget allows researchers to examine the effect of an activity on skills development conditional on other activities. Keane, Krutikova, and Neal (2020) for four developing countries show that spending more time in educational activities rather than work is beneficial for adolescents' cognitive skills, but less so if it is conditional on leisure time. Similarly, Jürges and Khanam (2021) show how more time spent in educational activities rather than screen time is beneficial for Australian adolescents' cognitive and socio-emotional skills. However, the authors find that more time in education instead of physical activity does not improve adolescents' skills.

On the flipside, adolescents can also adopt strategic behaviours and achieve so-called optimal time spent on certain activities. For example, engaging in 'good' levels of paid work and sleep, at the cost of leisure. Some studies call the ability to be more flexible in organizing one's time around different commitments the "Reconciliation Approach" (Passaretta and Triventi 2015), or it can also be conceptualised borrowing from the "Work-life balance" literature (the opposite coin of work-life conflict), which typically is used to explain the dilemma or possibility in balancing the two so-called separate spheres of 'work' and 'life' domains for working adults. Notwithstanding the fact that there is still no coherent concept of work-life balance and its complexities, 'work-life balance' follows more closely to the concept of 'work-family enhancement' or 'work family enrichment' (Greenhaus and Powell

2006). This line of research argues that taking on multiple roles can be beneficial as long as the roles are of good quality and the individual highly identifies with them. These studies illustrate how the effects of having multiple roles can show as rewards and skills from one domain (e.g., income or learning how to manage people) can help perform better in the other, as well as psycho-physical well-being and the quality of social relationships. In contrast to working adults, adolescents are able to engage in a more diverse set of activities, which if balanced well, could lead to enhanced social and emotional development, as they learn how to better navigate competing responsibilities in their lives.

Lastly, in an attempt of understanding how one may achieve an optimal or balanced set of activities to allow enrichment, the question of "how much is too much?" is always present. It may be that every additional hour of paid work may lead to greater or worse mental wellbeing, which assumes a linear relationship between the time spent in the activity and adolescent outcomes. There may also be a non-linear relationship where few hours of paid work are may be helpful for adolescents' social and emotional development via new experiences and the ability to mix, but excessive levels of work may be harmful for mental wellbeing.

1.5 The role of sex and socio-economic background

In relation to these "Activity" and "Time Resource" Mechanisms, I acknowledge that there are factors which would bring variation to these associations. Referring back to Figure 1.1, I focus on three major factors; (1) "Internal factors" which as most literature suggests, adolescent's time use are determined jointly by the adolescent and their family (Fiorini and Keane 2014; Del Boca, Monfardini, and Nicoletti 2017). (2) "Pre-determined factors" such as genetic factors passed on between parent and child (mental health or physical conditions passed on), as well as the sex of the adolescent. Lastly, I acknowledge (3) "External factors" such as the environment, shocks, and other individuals also determine the adolescent's time use directly, or through the internal factors. In these thesis I will focus on factors (1) and (2), but acknowledging factor (3) is useful in relation to the first two factors.

As I have discussed briefly in earlier sub-sections, time is not created equal and reflects inequalities in power. Such inequalities are most prevalent in differences in resources, reflected by socio-economic background such as parental education and family income (indicated by "Internal" factors in Figure 1.1) and by gender (indicated by "Antecedent" factors in Figure 1.1). I elaborate more below.

1.5.1 Socio-economic background

Adolescent's socio-economic background is inevitably linked to their parents or family income, education, and resources. Studies have shown that adolescent's socio-economic background is related to how adolescents manage their time, as well as their levels of self-esteem, self-efficacy, and mental wellbeing. There is a positive socio-economic background gradient and higher self-esteem, self-efficacy and mental wellbeing which can be explained by better social support and networks, and genetic mental health (Veselska et al. 2009; Borga, Münich, and Kukla 2021; Hazell et al. 2022). Hazell et al. (2022) also noted that there may be a transmission of mental health disorders from parent to child, as parents from lower socio-economic backgrounds report lower mental health of their child. Adolescents from lower socio-economic backgrounds may also have lower self-determined goals (Hitlin and Johnson, n.d.; Nunes et al. 2023; Schoon, Nasim, and Cook 2021).

Resource, such as family income, is directly related to adolescent's decision to engage in certain activities. Studies have shown that adolescents from higher socio-economic backgrounds have varied leisure activities (Kennewell et al. 2022; Gracia, Bohnert, and Celik 2023), are less likely to engage in economic work (Mortimer 2003; Burston 2017), spend more time in education-related or enrichment activities (Olds et al. 2023; Caetano, Caetano, and Nielsen 2024), and less time in unpaid or domestic work (Olds et al. 2023). This then brings us to the "Time resource mechanisms" where on the one hand, adolescents from lower socio-economic background may be less able to balance different spheres of activities (e.g., paid work and school), becoming time poor, because they need to engage in paid work for financial reasons. Adolescents from lower socio-economic backgrounds may also not be able to feasibly balance these activities, and thus completely commit to the less "standard" activity i.e., engaging in paid work early, and dropping out of education. On the other hand, adolescents from higher socio-economic backgrounds may be engaged in 'too many' varied activities, making it difficult for them to have any unstructured time (e.g., Caetano, Caetano, and Nielsen (2024) on too much "enrichment" activities as above).

Lastly, adolescents' socio-economic backgrounds are also influenced by their parents' actions. Families with lower resources may be working jobs that have more shifts and erractic schedules, making it difficult for parents to spend time with their children. This may implicate parenting styles. Parents from lower socio-economic backgrounds, who have less time availability, may be more flexible (e.g., allows child to go out to work or play with friends more) while parents from higher socio-economic backgrounds may be more authoritative. However, the reverse may also be true if parents from lower socio-economic backgrounds are not working. Studies have shown that parenting styles is associated with adolescents' self-esteem (Mogonea and Mogonea 2014), life satisfaction, and depression (Peng et al. 2021). In addition, parents from higher resources may be more able to provide access to a diverse set of time use opportunities such as mobile phones, access to cultural activities (theatres, movies), extra-curricular classes and allow adolescents. Parents with higher education may also be more aware of certain risks, such as media practices, compared to parents with lower education (Livingstone and Helsper 2007; Livingstone et al. 2015).

1.5.2 Gender

Gender differences – and here I clarify we are talking about biological sex and not gender identity – are evident in adolescents' division of time from a young age, as well as gender inequalities in mental wellbeing, mental health, and social and emotional outcomes.

Gender is a crucial factor in that how girls' and boys' time are divided early in the life course (Solaz and Wolff 2015). Prior research highlights the importance of gender role socialization, wherein children absorb gender-typical expectations from various sources such as family, school, community, and media. Consequently, they adopt and replicate gendered behaviors through daily interactions with individuals and societal institutions (Goffman 1977; West and Zimmerman 1987). In Figure 1.1, this is indicated by "External" factors, which influence "internal" factors (how adolescents decide to divide their time), reflected by their gender, the "Antecedent" factor.

Gracia et al. (2022) show that for adolescents aged 10 -17 across Finland, Spain, and the UK, girls spend more time on domestic work, personal care, and non-screen educational activities. Boys spend more time on screen-based activities and exercising. They argue that post-industrial societies structure children's daily routines could influence gender differences in children's activities. Therefore, in countries where young people are strongly encouraged to participate in their own leisure activities with peers or alone (outside families and schools), children could have more space to 'do gender' in their free time, and in ways that do not necessarily reflect their country's gender equality levels. These gendered differences are also likely to persist across time. For example, Matulevich, Carolina, and Viollaz (2019) analysed time use patterns of men and women for 19 countries (low- and high-income countries inclusive) between 2006 and 2014 and show that women spend more time in unpaid domestic work and men spend more time in paid market work. Matulevich, Carolina, and Viollaz (2019) find that this gender gap persists across the life-cycle; from 15 to 19-years-old until 65-years-old.

This division may result in boys and girls engaging in distinct activities with varying levels of intensity, consequently fostering inequalities in outcomes. For example, girls often undertake more domestic work, which may be perceived as less fulfilling for adolescent self-esteem and self-efficacy, given its necessity-driven nature. This is especially the case for developing countries, where girls are 'expected' to help in domestic work. These gendered differences may also reflect what girls and boys are not doing. If say, girls are not spending as much time on physical activities than boys, then they may be more sedentary or not being physically healthy, which is correlated to their mental wellbeing too.

There may also be socio-biological factors, such as age of puberty, which usually occurs earlier for girls than boys (Dahl et al. 2018). Early puberty means early physical maturation, which may result in conflicting feelings about self-representation, and being more vulnerable to comparisons to peers. This could mean that girls compared to boys, may feel more vulnerable to activities that relate to social connectedness with others, such as being on social media or playing with others, and is likely strongly interlinked with the issues of gender role socialization discussed above. Studies have shown that girls usually have greater mental health disorders, lower life satisfaction, and lower self-esteem compared to boys in association with social media (Mcdool et al. 2020; McNamee, Mendolia, and Yerokhin 2021; Banthorpe et al. 2020; Kelly et al. 2019), but evidence about this relationship with other activities are scarce.

Lastly, there may also be intersectionalities between socio-economic background and gender. Greater socio-economic background may be a protective factor for vulnerabilities by gender. If girls are disproportionately negatively affected by certain activities (e.g., social media), girls from families with better physical and emotional resources may help to combat these negative associations, either through providing better alternatives to the activity (e.g., outdoor and healthy social activities) or emotional support. Hervé et al. (2021) found that small gains in adolescents' cognitive and socio-emotional competencies can be improved from improving gender attitudes, but larger gains are made from improving household socio-economic status, suggesting there is a strong gradient, or at least contributions to socio-emotional development through socio-economic status. On the other hand, it is possible that there may not be any gradients by socio-economic status. Gruijters, Raabe, and Hübner (2023) recently found that disadvantaged children had comparable academic returns from socio-emotional skills as advantaged children. The explained share of the learning gap is small because differences in socio-emotional skills between the low- and high-SES groups are not that large. Both groups exhibit notably high levels of school-relevant socio-emotional skills.

1.6 Adolescent time use and development across countries and age

The majority of individuals in most cultures in the 21st century typically undergo similar life events between early adolescence to adulthood (e.g., entering school, graduation, obtaining a job, and family formation), but the ages at which they transition into each life event, which in turn implicates how their time is spent, differs by country and socio-cultural norms. The ILO (2021) show that 160 million children and adolescents aged 5 to 17 globally, typically in sub-Saharan Africa, Asia and the Pacific, and Latin America and the Carribbean, are doing some form of paid or unpaid work. While more boys are engaged in work than girls, girls shoulder the majority of the burden of domestic work. In Western countries such as in the UK, adolescents do engage in unpaid and paid work, but these are typically at later ages, during secondary school or later.

While this thesis does not directly compare findings across countries, it demonstrates that adolescents in different countries face similar constraints and choices which are relevant for policy aims. For example, the cost and benefits of work during studies are relevant for 15 year olds in the Global South, as it is during university in the UK.

In high-income nations, adolescents from families with higher socio-economic status compared to those of low socio-economic status, typically engage in greater amounts of moderate-to-vigorous physical activity (Stalsberg and Pedersen 2010) as well as non-screen sedentary activities such as reading, playing musical instruments, drawing, and doing homework. Conversely, they spend less time on screen-based sedentary behaviors like watching television and playing video games, which are often linked to adverse effects on cognitive and socio-emotional development, as well as mental health. In developing countries, these differences in socio-economic status may instead be reflected by location (urban or rural localities), hours spent attending school, or different kinds of work (stone crushing or helping out with the family shop). Adolescents who are less advantaged, regardless of country, are more likely to work and study. The risk of exclusion or inequality in education-related experiences are present, but the contexts in different countries show us the differences in risk associated with engagement in certain activities, how it affects the rest of the time adolescents are involved in, and how it is associated to their socio-emotional competencies. For example, the ‘choice’ in engagement in domestic work compared to the ‘choice’ in doing paid work in the UK during university.

Examining how time is divided across ages demonstrates an important cross-national differences in how adolescent’s autonomy, independence, and intensity in activities (and in relation to their outcomes). In developing countries such as in India and Ethiopia, adolescents are already expected to contribute to the family as a unit, compared to early adolescents in the UK, which implicates what they do in their free time. However, the way most studies examine adolescent time use in developing countries still focus on the dilemma of paid work, with less attention on 'leisure' or 'free' time, often categorized as one lump sum category. In developed countries, issues of social media and watching TV is a concern, which is in fact, leisure time, but does not seem to be cause for concern in developing countries. Hence, there needs to be more holistic analysis of adolescents' time use in different contexts. There are also different social norms and expectations, which means the 'choice' in engaging in certain forms of activities are 'expected' and 'usual' – while work can be degrading (depending on the type of work), work in a high-risk situation may instead be seen as a 'good' thing. While conditions are much safer for adolescents to work in developed countries, the stigma and pressure around work in itself may not be helpful for adolescents' outcomes. For example, teenage marriage is relatively high in India, and there is a strong expectation that girls need to engage in domestic work early as part of their pathways to growing up, where they are not only expected to attend school, but also be of good marriageable prospects (basically, it's not a trade-off between getting married or going to school, its kinda like do both).

Therefore for Chapter 2, I examine the associations of paid and unpaid work, attending school, study, and leisure in developing countries at younger adolescence, but in Chapter 3 I examine a time when adolescents in developed countries have higher prevalence of work, that is, during late adolescence when they are in university. Based on the previous chapters, I found that 'leisure' was often a disregarded activity, and thus in Chapter 4 examined a form of leisure activity in detail i.e., screen time.

Studies have highlighted the importance of differences in socio-cultural norms in explaining variations in gender gaps of time use and socio-emotional competencies and well-being across countries. The 'gender equality' hypothesis argues that gender equality at the country level brings higher gender symmetry in child time use. This hypothesis expects boys and girls in more gender egalitarian countries show similar time-use patterns across gender, because expected gender gaps in adults' and societal time use and values will be reproduced among children. For example, if adults exhibit more egalitarian behaviours in domestic work and gender norms, these gender inequalities among adults might be transmitted to the younger generations via intergenerational socialization processes, which in turn might lead to smaller gender differences in child and adolescent domestic work one country compared to another. Gracia et al. (2022) find evidence for this, where gender gaps in children's time use were smaller in a more 'egalitarian' Finland than in 'liberal' UK, but especially so compared to 'family-oriented' Spain, and children's time use mirrors cross-national variations in adults' time use and gender roles.

On the other hand, the 'child autonomy' hypothesis argues that it may be that national contexts influence adolescent's gendered time use through how adolescent's daily routines and free time are organized, regardless of gender egalitarian policies and norms at the national level (Rees 2017; Hook 2006; Kan, Sullivan, and Gershuny 2011). Studies found that post-industrial societies with marked 'self-expressive' values emphasizing individual autonomy display strong gendered educational preferences, irrespective of gender equality levels (Cech 2013; Charles and Bradley 2009; Stoet and Geary 2018).

Gendered variations in socio-emotional competencies are also evident across countries, especially different in non-Western contexts. In a study of 48 countries to include countries beyond just Western samples, including countries like Costa Rica, Peru, Malaysia, and the Philippines, Bleidorn et al. (2016) find that men report higher levels of self-esteem than women, which suggests there are 'universally sociocultural factors' that influence global self-esteem similarly across nations, such as universals in socially learned roles and stereotypes (Williams and Best 1990; Wood and Eagly 2000). However, the authors also found significant variations in the magnitudes of age and gender-specific trajectories such as difference by the nation's mean age at marriage, GDP per capita, and HDI, which may be explained by the 'gender equality' or 'child autonomy' hypothesis. The authors also add that these differences may be based on cultures where there is a cultural emphasis of girls' and women's physical appearance, and cultural pressures during adolescence can have particularly negative effects on self-esteem (Brumberg 1997; Kling et al. 1999).

Growing literature show that the pathways in which time use and adolescents' socio-emotional competencies in non-Western countries may differ to Western countries, but also it is not a clear division between so-called 'developed' and 'developing' countries, nor is there a clear division between the Global North and South, but rather differ by country. Wanless et al. (2013) show that the gender difference in behavioral problems observed among school children in the US is not observed in Asian societies like Taiwan, South Korea and China. In China, males are more prone to have lower self-esteem and suffer from more severe depressive disorders than females during college (Gao et al. 2022; Al-Qaisy 2011). Dercon and Singh (2013) in fact show that girls fare worse than boys on agency and self-esteem in both India and Ethiopia, with a striking pro-male bias in agency. However, there is still a large gap in evidence about non-WEIRD (Wester, educated, industrialised, rich and democratic; (Henrich, Heine, and Norenzayan 2010)) country contexts, and in this thesis, I also show how there are variations in these relationships across countries that are all considered 'developing'. For example, while countries can all be classified as 'developing', some may be less agricultural based than others. Focus on education is also different across countries; there is a strong policy in Vietnam for enrollment (and high PISA scores), and in contrast, it is common for adolescents in Ethiopia to enrol in school late.

1.7 Estimation challenges and strategies

There are two main challenges in estimating causal empirical relationships between adolescent time use and their outcomes. I will discuss them here, and will show how they relate to my specific research questions in each chapter. First, there is unobserved heterogeneity. That is, there are differences between adolescents that are not observable which may affect their outcomes and/or time investments. For example, suppose I am interested in the relationship between paid work and self-esteem for adolescents at age 18. There are two adolescents who differ because one is a gifted communicator, while the other is not but this ability is not observed by the researcher. The "more gifted" adolescent may allocate time differently to, e.g., paid work rather than school, as well as have greater self-esteem because s/he finds it easier to establish their social standing amongst peers. Referring back to Figure 1.1, this can be visualized by the arrow between the “Antecedent” factor which is not observed, towards the “Internal” factors. Not accounting for such unobserved ability may overestimate the coefficient estimate of the effect of paid work on self-esteem. We can also imagine many other unobservable characteristics which may bias estimates upwards or downwards (e.g., parent preference towards paid work).

Secondly, there is reverse causality. It is highly likely that adolescents’ mental well-being also in turn determines adolescents’ time allocation. Using the same example as above, adolescents with higher self-esteem may choose to do more paid work because jobs for youths tend to be in the service sector and require good communication. Therefore, an estimate of the effect of paid work on self-esteem may instead be in the reverse direction (this is indicated by the two-way arrows in Figure X between time use and outcomes, and also how the “Antecedent” factor can be related to both the adolescents’ time use and outcomes).

To partly address both these challenges, a lagged dependent variable (LDV) can be included in the model. To account for unobserved heterogeneity, the LDV is a proxy for unobservable ability (e.g., communication aptitude) and other previous unobservable inputs. The introduction of longitudinal data – data in which information is observed repeatedly across time for an individual – enabled the use of LDVs as explanatory variables to account for unobserved heterogeneity (Ashenfelter 1978). Using the same example as before, this lagged variable might be self-esteem at age 16. The argument is that self-esteem at age 16 captures previous decisions made by the adolescent and his/her parents that produced self-esteem at age 16, even if these decisions were influenced by unobservable factors. For instance, if parents and adolescents preferred to allocate the adolescent’s time more in the family business and less time for school because of any of the unobservable factors, then the result of this preference will be reflected in the self-esteem score at age 16. This estimation strategy is often called the value-added (VA) model or LDV models.

Recent research has used LDV models to examine the relationship between children’s time investments and their cognitive and socio-emotional skills (Cunha et al. 2006; Del Bono, Kinsler, and Pavan 2020; Fiorini and Keane 2014; Todd and Wolpin 2007). Investments made during the prenatal period produce skills at childhood, which in turn influence investments made during childhood which then produce skills at adolescence, and so on. To explain how the LDV or VA model helps account for unobserved heterogeneity, I borrow an example from Todd and Wolpin (2007). Let us assume that if we had access to all available information for adolescents, the "true" structure of adolescent's skills acquisitions is the following for each adolescent in each household:

To explain how the LDV or VA model helps account for unobserved heterogeneity, I borrow an example from Todd and Wolpin (2007). Let us assume the 'true' structure of children's skills acquisitions is described by the following equation for each child in each household:

$$\begin{aligned} Y_a = {} & \alpha_1 X_a + \alpha_2 X_{a-1} + ... + \alpha_a X_1 \\ & + \rho_1 v_a + \rho_2 v_{a-1} + ... + \rho_a v_1 + \varepsilon_a \end{aligned} \tag{1.1}$$

where Y represents skills at age a. X_a and v_a are observed and unobserved inputs at age a. ε_a is the residual error term. To fit this model, I assume that the production function is approximately linear. The equation states skills acquisition at age a is determined by all current observed and unobserved characteristics at age a, and prior inputs before age a. However in real world datasets, not all the variables are observed at every age. As a result, we use the LDV approach, and assume the following measurement equation:

$$Y_a = \gamma Y_{a-1} + \alpha_1 X_a + e_a \tag{1.2}$$

As discussed, Y_{a-1} is used to proxy for all prior observed and unobserved inputs up to age a. For this approach to lead to good estimates of the effects of the factors included in X, the measurement model has to be a good approximation. For this to occur, several assumptions need to hold. To show what these are, subtract γY_{a-1} from both sides of model 1.1, which gives us:

$$\begin{aligned} Y_a = {} & \gamma Y_{a-1} + \alpha_1 X_a + (\alpha_2 - \gamma\alpha_1) X_{a-1} + ... + (\alpha_a - \gamma\alpha_{a-1}) X_1 \\ & + \rho_1 v_a + (\rho_2 - \gamma\rho_1) v_{a-1} + ... + (\rho_a - \rho_{a-1}) v_1 \\ & + \varepsilon_a - \gamma\varepsilon_{a-1} \end{aligned} \tag{1.3}$$

For model 1.3 to reduce to model 1.2, we need for all k, $\alpha_k = \gamma\alpha_{k-1}$ for observed characteristics, and $\rho_k = \rho_{k-1}$ for unobservable characteristics. Since γ is the common factor between current and previous values of an input, we assume $\gamma < 1$ because it is unlikely that prior inputs have the same or greater impact on current outcomes ($\gamma = 1$ or $\gamma > 1$). This means that the *coefficient estimates* of observed and unobservable inputs (including gifted ability) on skills formation decline geometrically with age.[2] That is, the effect of paid work at age 16 (and unobserved preferences and abilities) has a larger impact on self-esteem at age 16 than at age 18, and the effect declines across age at a constant rate. The model also requires that the error term is serially correlated and the degree of serial correlation matches the rate of decay of the input effects, γ. Therefore, causal interpretation of these relationships using such models require these strict set of assumptions, which could be violated.

To account for some reverse causality, the LDV model relaxes the strict exogeneity assumption and instead assumes sequential exogeneity. Ordinary Least Squares (OLS) estimators require strict exogeneity to interpret the causal effect of time use on adolescent outcomes, that is, time use must not be correlated to any past, present, and future values of adolescent outcomes which in essence means that reverse causality cannot exist. Sequential exogeneity on the other hand, assumes that the variable of interest, e.g., paid work, is uncorrelated to past values of adolescent outcomes, but can be correlated with future values of adolescent outcomes. In essence, the LDV model maps the interplay between the dependent and explanatory variables over time by using lagged values of the dependent variable on the right hand side of the equation (as in model 1.2).

However, one can still imagine a case where prior adolescent outcomes may still affect how adolescents spend their time currently and thus the model does not fully account for the issue of reverse causality. Previous studies using panel data have employed lagged explanatory variables instead to account for the issue of reverse causality. Bellemare, Masaki, and Pepinsky (2017) show that while this method removes the assumption of strict exogeneity, it also introduces a similarly strong and untestable assumption that unobserved variables are serially uncorrelated. That is, replacing the current explanatory variable with

[2] If we substitute γ=0.5 into model 1.3, we can see that the coefficient for historical observed inputs are α_2=0.5α_1, α_3=0.5$^2\alpha_1$, α_4=0.5$^3\alpha_1$ and so on.

the lagged version of itself simply moves the endogeneity problem one time period backwards. Therefore, causal identification using lagged explanatory variables usually impose as strong assumptions as models with contemporaneous values of explanatory variables, and can also lead to misleading inferences. Bellemare, Masaki, and Pepinsky (2017) recommend that lagged explanatory variables could be useful in causal identification only under strict assumptions, including assumptions that the causal effect operates in a one period lag only, and that there are no dynamics in the dependent variable, but there are dynamics in the explanatory variable.

For the purpose of my research questions, using the LDV model is appropriate since the assumption about the model being dynamic likely holds. An adolescent's current set of competencies is a function of their previous set of competencies, as individuals learn competencies over time. This is also supported by previous work modelling adolescent time allocation on their developmental outcomes, always reporting estimates without and with LDVs (Del Bono, Kinsler, and Pavan 2020; Fiorini and Keane 2014; Keane, Krutikova, and Neal 2020). This reflects what is advised by Keele and Kelly (2006), that if the current value of the true or observed outcome of interest is a function of its previous values, then researchers should use OLS with an LDV, and they show that not including an LDV in a dynamic model leads to biased estimates. Wilkins (2018) re-ran and improved simulations by Keele and Kelly (2006), and supports the use of LDVs as a more robust estimator of the independent variable than without the LDV. In addition, Wilkins (2018) argues that residual autocorrelation can be corrected using additional lags of the outcome variable, in line with Leszczensky and Wolbring (2019) who argue for the need to specify the "correct" number of temporal lags. In my analysis, I control for previous values of competencies as well, to account for this.

Dafoe (2018) argues that LDVs should only be used under strict assumptions about unobserved factors, which are difficult to evaluate. He argues that LDVs should be used only if there are no unobserved common causes of treatment and the lagged outcome or no unobserved factors that affect both the outcome and lagged outcome. In other words, gifted ability is not a common factor of both paid work and lagged self-esteem, nor can it be a common factor for self-esteem and lagged self-esteem. Otherwise, including an LDV will induce bias. This assumption is likely violated in my analyses, but also difficult to evaluate given the observed data, especially in the case of socio-emotional competencies – a concept that is subjective. This is especially difficult when it is unclear whether the lags between panels in the observed data matches the real-world causal lags. In all my chapters, I conduct several robustness checks and use different estimations with different sets of assumptions to test for this. For example in Chapter 2, I conduct a fixed effect (FE) analysis which instead assumes that the unobserved factors are time invariant, and only examines the effects of the differences in variables that change across time. FE models assumes that these unobserved factors can be demeaned by subtracting unit-specific means from the dependent and explanatory variable. However, this technique can only be done with rich enough panel data with repeated measures across time. It also assumes strict exogeneity as discussed previously, which yield biased estimates in case of reverse causality. In Chapter 3 where I was limited by the dataset and could not conduct a FE analysis, I tried to minimize selection on variables as much as possible. I used inverse probability weighting approach to also account for a different set of assumptions on selection on observables to the VA model, and attempted to use instrumental variables to account for reverse causality but failed to find strong enough instruments (an instrument that causes variations on the full time use budget but not directly on adolescent's social and emotional outcomes).

Despite these concerns listed above, Caetano, Kinsler, and Teng (2019) have shown that using VA models to examine the relationship between parental time inputs and children's cognitive and noncognitive development that using a rich set of controls, together with a comprehensive list of time inputs, are able to absorb endogeneity from omitted variables, reverse causality and measurement error. Since the VA and LDV models can only be interpreted as causal under assumptions, and that the assumption about unobserved factors not affecting both dependent and explanatory variables (and their lags) is likely violated, I minimise the use of causal language and instead am showing new findings about the associations between time inputs and adolescent competencies and wellbeing. For example, the conclusions drawn from my findings do not argue that adolescents need to reduce paid work to improve their self-esteem, but rather, shows the nuances of how paid work in substitution of leisure is associated to self-esteem. While the VA and LDV models absorb as much endogeneity and reverse causality and measurement error as shown by Caetano, Kinsler, and Teng (2019), the presence of reverse causality still cannot be fully discounted. The main contributions of these analyses in each chapter examines which of these activities are associated with adolescents' socio-emotional competencies and wellbeing, examining time use in granular detail, and understanding the variations of these relationships across socio-demographic groups. In addition, given that I use birth cohort data in all my chapters, these findings are not generalizable to a wider population and instead shows the dynamics of how these relationships may occur over time.

1.8 Thesis outline

The remainder of this thesis consists of three sole-authored empirical chapters (Chapters 2, 3, and 4), plus a conclusions chapter (Chapter 5), discussing the findings of the empirical chapters. Each of Chapters 2, 3, and 4 addresses a research question about adolescents' time allocation and their socio-emotional competencies or mental wellbeing. In all three chapters, I use longitudinal birth cohort data which is useful for examining adolescents' trajectories across the life-cycle and to quantitatively estimate adolescents' outcomes using VA or LDV models. Chapter 2 uses data from four developing countries: Ethiopia, India, Peru and Vietnam. Chapters 3 and 4 use data from the UK.

In Chapter 2, I examine how adolescents' time allocation in four developing countries (Ethiopia, India, Peru, and Vietnam) is associated with two measures of socio-emotional competencies; self-esteem and self-efficacy. In a context where adolescents from poor families are expected to work and attend school, I study whether adolescents can build potential life skills through work or play. This study contributes evidence about how different adolescent time inputs relate to their socio-emotional competencies in developing countries, which has rarely been studied. I expand upon two earlier papers using the same data, Keane, Krutikova, and Neal (2020) and Borga (2019), showing evidence that it is not only one specific activity that matters for socio-emotional competencies development, but that the estimates of the association for one activity are contingent on how the total time budget is allocated. I also extend previous research by providing new evidence of the gender and country disparities in time use and socio-emotional competencies development.

In Chapter 3, I examine whether students develop life skills through paid work, an activity which disadvantaged students are more likely to do than their more advantaged peers. This study contributes to the student employment literature by documenting the association between paid work during university and socio-emotional competencies, which has not been studied before. Using longitudinal data for a cohort of English students born in 1989/90 (the Next Steps study), I model the development of university students' internal locus of control – the belief in one's ability to have control over their life events – between ages 14/15 and 20/21, and their time spent in paid work during university. In addition, this study contributes evidence regarding the UK, whereas most existing studies are about the USA and Canada.

In Chapter 4, I examine whether excessive amounts of screen time are associated with poorer adolescent mental wellbeing. Research to date has reported contradictory findings about whether more screen time is bad for adolescent mental wellbeing because it has used different definitions of screen time, and different measures of wellbeing, and examined different groups of teenagers. I distinguish four types of screen activity: social screen time, internet browsing, playing e-games, and passive video viewing. I measure well-being outcomes using measures of self-reported happiness and self-esteem, and parent-reported behavioural problems of their offspring. Using time diary data for 14-year-olds participating in the UK Millennium Cohort Study, I examine these relationships using models that control for adolescents' prior mental wellbeing and extensive background characteristics, and I show how these relationships differ by gender and parental education. This chapter shows that whether more screen time is bad for adolescent wellbeing depends on who reports their wellbeing, and which types of screen activity is examined.

In Chapter 5, the Conclusion, I summarise the findings of Chapters 2–4, and provide a critical discussion of the empirical findings of Chapters 2 to 4. Additionally, I review the implications and relevance of the findings for policy and data, as well as for future research.

Overall, the thesis makes several contributions under three broad themes. Firstly, it pays special attention to socio-emotional competencies and wellbeing as outcomes of interest, adding evidence to our knowledge about how these outcomes are formed. Second, the thesis highlights the value of examining time use in detail and examining activities across the full time budget. Lastly, it provides a new integrative framework in examining how activities (whether singularly or across the time budget) is associated with adolescents' socio-emotional competencies and mental wellbeing.

Chapter 2

How is adolescents’ time allocation associated with their self-esteem and self-efficacy? Evidence from four developing countries

Abstract

Adolescents' time allocation is an important determinant of socio-emotional skills formation, but evidence from developing countries is limited. This study builds upon two previous studies using data from four developing countries. I estimate how adolescents' time allocation determines two measures of socio-emotional skills; self-esteem and self-efficacy. I also show how these estimates are sensitive to trade-offs across different types of activities. In every country, an additional hour of domestic work that reduces time for school or study reduces adolescent's self-efficacy, significant for all countries except Peru. Work is most harmful for girls in India and Vietnam, but not for boys in Ethiopia. However, domestic or economic work that shifts time away from leisure is no more or less determinative of adolescents' self-efficacy or self-esteem in all countries analysed. Attending school and studying outside school improve both self-efficacy and self-esteem for adolescents in Peru, but are statistically insignificant in the other three countries. Overall, these findings are mainly relevant for self-efficacy compared to self-esteem. The harmful effects of adolescents' work are contextual, depending on the activities within the time budget, and the country studied.

This article is published as Chang (2022) at the Journal of Development Studies. Edits are made according to examiners' comments.

2.1 Introduction

socio-emotional skills are found to be important predictors of future education, labour market and social outcomes in Europe and the USA (Heckman, Jagelka, and Kautz 2021; Almlund et al. 2011; Heckman, Stixrud, and Urzua 2006). Given their importance, there is growing research interest in examining the determinants of socio-emotional formation at childhood. Studies in Australia, Europe and the USA find that adolescents' skills formation is determined by how parents spend time with their children, and how they allocate adolescents' time (Caetano, Kinsler, and Teng 2019; Del Bono et al. 2016; Fiorini and Keane 2014; Hsin and Felfe 2014). For developing countries, evidence of this relationship is scant. Challenges stem from a lack of both data, and valid measures of adolescents' socio-emotional skills, and that adolescent's everyday activities in developing countries involve domestic and paid work. In developing countries where adolescents may face barriers to access and to quality schooling, important life skills may be fostered during various activities, including work and play. This paper studies the relationship between activities adolescents typically perform and the formation of two most commonly measured constructs of adolescent socio-emotional skills – self-esteem and self-efficacy – in four developing countries. In comparing adolescent time use across four countries, I avoid stereotyping adolescent time use in "developing countries." Across Ethiopia, India, Peru, and Vietnam, there are diverse labor, education, and gender norms. In Ethiopia, adolescents start school later, while in both India and Ethiopia, gender biases are greater. Peru and Vietnam in comparison have better educational policies. However, Vietnam faces the challenge of earlier male school dropout rates.

There are two drawbacks to existing studies linking adolescents' time allocation and their skills formation in developing countries. One, most studies examine adolescents' time allocation solely as the trade-off between working and school attendance. However, work and school are not the only two activities adolescents engage in. Recent work by Keane, Krutikova, and Neal (2020) demonstrates that treating school attendance as the only counterfactual to work overestimates its negative effects. Second, few empirical studies examine socio-emotional skills as an outcome of interest for adolescents' human capital development, despite having been advocated by (Heckman, Jagelka, and Kautz 2021) as an important component of human capital accumulation as cognitive skills. The only study I am aware of that uses socio-emotional outcomes is by Borga (2019) who uses Young Lives (YL) data from 2009, to examine both cognitive and socio-emotional skills. He finds that undertaking paid work and unpaid family work (i.e. household tasks, not including domestic work) are detrimental to adolescents' socio-emotional skills in Ethiopia, India and Vietnam.

My study contributes to the literature by linking these two gaps and build upon these two key studies cited, using YL data (Keane, Krutikova, and Neal 2020; Borga 2019). I extend Borga's work, demonstrating the importance of examining trade-offs across different types of activities when analyzing the relationship between time inputs and skills formation (following Keane, Krutikova, and Neal (2020)). I contribute evidence about how adolescent time inputs are important determinants of skills in developing countries, where evidence is scarce because of greater focus on direct parental inputs, cognitive skills, and the majority of evidence are in developed countries. I extend on Keane, Krutikova, and Neal (2020) by giving special attention to measures of socio-emotional skills, important because these skills form differently to cognitive skills. For example, socio-emotional skills are more sensitive to environmental influences at later ages (Borghans et al. 2008) and more studies are still required to examine the evolution of socio-emotional skills across the life cycle (Heckman, Jagelka, and Kautz 2021). In addition, I make two further extensions to work by Borga (2019). First, I use an updated cohort (2001/02 instead of 1994/95) with better validated measures of socio-emotional skills.[1] The younger cohort represent adolescents who are more likely to attend school and less likely to do paid work, but hidden unpaid work are still prevalent despite lower participation in paid labor. Second, I examine an additional YL country, Peru, which is valuable because, unlike the other three countries, the sample is nationally representative, and provide an important narrative from a primarily urban sample (rather than primarily rural).

Using longitudinal YL data in Ethiopia, India, Peru and Vietnam, I examine the re-

[1] Yorke and Portela (2018) report on the validity and reliability of the scales and find that in previous rounds of the data (Rounds 2 and 3), the statements 'Other people in my family make all the decisions about how I spend my time' and 'I have no choice about the work I do - I must do this sort of work' is negatively correlated with other items of the scale. The authors suggest that adolescents may view these statements positively, where obedience may be an attractive attribute. This means that these statements were interpreted differently and the scale is not parsimonious.

lationships between five types of activities from adolescents' full time budget: (i) domestic work (ii) economic work (iii) leisure (iv) attending school and (v) studying outside school, and their generalised self-esteem and self-efficacy. Generalised self-esteem measures the extent the individual views him/herself favourably, and generalised self-efficacy measures the general belief in one's own ability to overcome challenges. Despite being related, these two measures are conceptually distinct (Bandura, Freeman, and Lightsey 1999; Chen, Gully, and Eden 2004). Self-efficacy captures more of a motivational belief regarding task capabilities while self-esteem captures more affective components (Chen, Gully, and Eden 2004). Both these concepts are important in the context of adolescent's activities in developing countries, as qualitative evidence in often cite both self-esteem and self-efficacy as 'life skills' adolescents could learn through paid and unpaid work especially when cost-benefit decisions of attending work or school is high.

However, the narrative is often framed in an environment where young people are at risk, and thus there is a delicate balance between gaining independence (and hence, social emotional competencies) and being marginalised. Risk holds the potential to enhance adolescent's social learning from the importance attached to adolescent's self-reliance, which in turn strengthens their capacity to contribute to their households. Rogoff (2003) terms this 'interdependent autonomy' where participation in work means that children and adolescents become more independent, and in turn gain skills which are their so-called insurance against risk. Risk reduction however, can also be achieved via education, which is expanding in these communities. Therefore, while engaging in work may help raise independence, it may also do the opposite if it comes at a cost for long-term risk mitigation such as education. For example, evidence shows that economic work at the cost of education is often associated with poorer self-esteem, as adolescents feel ashamed to not join their peers at school or are in laborious work (Tafere and Pankhurst 2015; Boyden, Porter, and Zharkevich 2021). However, what is less studied is the implications if leisure time is substituted instead, which may allow the adolescents to balance both work and studies. Given this, I expect to see the following with my analyses. First, more time in any work at the cost of educational activities (attending school or studying) is associated with lower self-esteem and self-efficacy. Second, this magnitude is smaller if any work comes at the cost of leisure. Third, more time attending school instead of work is associated with improved self-efficacy and self-esteem.

Given that work is highly gendered, with girls doing more unpaid work and boys doing more paid work, I also expect to see that these associations are larger in magnitude if girls and boys perform more of the work according to their 'gender role' instead of schooling. In addition, studies have showed that when gender roles are reversed (i.e., boys doing a 'girls job'), then this act can be seen as shameful, and thus I expect to see lower self-esteem when boys do more domestic work, and girls do more economic work, at the cost of either leisure or school. Lastly, rural and urban locations may provide different opportunities for education and the types of work. Thus, I examine these associations between work and education by locality, expecting trade-offs to be smaller in urban areas.

Following methodology by Keane, Krutikova, and Neal (2020), I model adolescents' self-esteem and self-efficacy production at age 15 based on their time allocation using extended value-added (VA) models. Extended VA models are widely used in the literature on adolescent's human capital accumulation, reflecting inputs made throughout the adolescent's life up to the specified period (Cunha and Heckman 2008; Todd and Wolpin 2007). The models partially account for unobserved heterogeneity by using lagged skill scores to proxy for the adolescent's ability, and parental investment decisions conditional on the adolescent's ability. The model is only causal under strong assumptions, which may not necessarily hold. While not causal, my study sheds new evidence on the direction of the relationships between adolescent's activities and measures of socio-emotional skills.

My findings show that domestic work is the "more harmful" type of work for adolescents' skills, and estimates are more relevant for self-efficacy than self-esteem. Economic work is also associated with lower self-efficacy, but is statistically insignificant in all countries except India. Work is more detrimental to girls' skills in India and Vietnam, but more detrimental for boys in Ethiopia. Beneficial activities such as attending school and studying outside school are statistically significant for adolescents' self-esteem and self-efficacy, but only in Peru, and the associations are driven by girls. Moreover, I find that work may be no more or less productive than leisure time. In all countries, neither form of work that shifts time away from leisure is statistically significant or has near zero associations to self-esteem or self-efficacy. In Peru, an additional hour of leisure instead of attending school is significant and negatively associated with both self-esteem and self-efficacy. In sum, domestic work is harmful for adolescents' self-efficacy if it shifts time away from attending school, but the benefits of other activities such as leisure and educational activities depend on the country, and the activity contingent upon the activity of focus.

2.2 Hypothesised Mechanisms

Examining both self-esteem and self-efficacy is advantageous because they may vary based on the activities adolescents engage in and the activities substituted, but evidence for these variations are scarce. Qualitative evidence in developing countries often name both self-esteem and self-efficacy (or similarly related measures) as the life skills adolescents learn through paid and unpaid work in developing countries, such as feeling a sense of belonging and pride to the family, to feel like a responsible contributor to the family, to build resilience during stressful situations, but also nuance how it depends on whether work conflicts with school time or time with peers (Abebe 2007; Pankhurst, Crivello, and Tiumelissan 2015; Aufseeser et al. 2018; Boyden, Porter, and Zharkevich 2021). For example, while Abebe (2007) find that adolescents begging in Ethiopia consider this a shameful activity, but also largely acknowledge that it helps them feel a sense of shared responsibilities for their family and acknowledge this is a temporary survival strategy to better outcomes.

There are several ways in which adolescents' activities may matter for their socio-emotional development. According to Rogoff (2003), adolescents can learn to navigate and manage risks effectively within their cultural environments, contributing to their overall development and competence. Hence, the way activities may relate to socio-emotional skills depends on the type of activity, the environment, and the culture surrounding the activity.

First of all, there may be productive activities e.g. attending school which improve socio-emotional competencies through education or interaction with peers and role models. More time in work that reduces time attending school may mean less time to gain from these beneficial activities. Some studies in developed countries support the conclusion that educational and socialisation activities are important in improving adolescents' skills. Del Bono et al. (2016) for the UK and Hsin and Felfe (2014) for the USA find that a mother's time spent with the child (up to age seven and 12 respectively) such as reading to the child or playing music, improves adolescents' cognitive and socio-emotional outcomes. However, studies also find that different activities may matter for different skills. Fiorini and Keane (2014) find that for Australian adolescents aged one – nine, educational activities such as being read to and playing educational games improve adolescents' cognitive skills, but not their socio-emotional skills.

Conversely, there may be unproductive activities. Adolescents' work in developing countries may be difficult and stressful, and more time spent in work could hinder their development. Research on child labour has mainly focused on adolescents' cognitive skills as the main outcome of interest and presents conflicting evidence, depending on the country studied and empirical strategy. Studies that use fixed-effects estimates find that child labour reduces adolescents' cognitive skills, measured by mathematics and language test scores (Emerson, Ponczek, and Souza 2017; Gunnarsson, Orazem, and Sánchez 2006). Dumas (2012) however, using an instrumental variables strategy finds no evidence of a negative relationship between past years of work for adolescents in Senegal and their cognitive achievement measured by French and mathematics scores eight years later. She even finds a positive impact of adolescents' work on oral mathematics scores. Studies in YL countries show that work is highly gendered; girls tend to do more unpaid work while boys tend do more paid work. Morrow and Boyden 2018 show that boys are involved in more physically demanding and risky work, which may negatively impact their self-efficacy. For example in India, boys in agriculture work on physically demanding activities such as ploughing, sowing and marketing whereas girls undertake activities such as transplanting, harvesting and bundling. Girls are confined to more domestic tasks, typically due to gender norms (e.g. girls are expected to learn how to cook and clean to 'care for the household'), but also due to gendered safety concerns such as physical safety and reputation.

Work may also provide important adult and peer socialisation opportunities for adolescents. This opportunity may be especially important for poor families where socialisation with family members take place during household chores or tending to the family farm or business. Qualitative studies such as by Morrow and Boyden (2018) based on YL countries argue that adolescents and parents see economic work as a way to gain knowledge and learn new practical and social skills such as establishing a foothold in the labour market, and learning responsibility as 'part of their adulthood'. Given the gendered allocation of work, adolescents may be expected to perform certain 'gender roles', which may be detrimentally related to their self-efficacy if adolescents feel that they have no choice but to do this work. Studies also show that adolescents who perform the opposite gendered role may have lower self-esteem, for example, boys doing unpaid domestic work may feel ashamed to be doing a 'girls' job' (Boyden, Porter, and Zharkevich 2021).

Gender differences in the types of work means that exposure to risk may vary by gender. Boys who are typically engaged in market work may be more exposed to physically demanding work, while girls who are typically engaged in domestic work may be more vulnerable to physical, verbal, and sexual abuse because of the isolating nature of domestic work. YL qualitative work by Morrow and Boyden 2018 show that boys are involved in more physically demanding and risky work. For example in India, boys in agriculture work on physically demanding activities such as ploughing, sowing and marketing whereas girls undertake activities such as transplanting, harvesting and bundling. Girls are confined to more domestic tasks, typically due to gender norms (e.g. girls are expected to learn how to cook and clean to 'care for the household'), but also due to gendered safety concerns such as physical safety and reputation. Roest (2016) also highlighted that young men's ability to work in the fields in Peru are highly valued in a rural context, because they are stronger than young women and have more previous experience in the fields. These gender expectations and preferences to different activities in childhood could result in a self-perpetuating cycle for the child. For example, boys are expected to work in the fields, end up doing so and become skilled at it, and continue doing so later in their adolescence.

Leisure is also rarely explored as a determinant of adolescents' skills development in developing countries. In developed countries, studies in pediatrics argue that constructive play enhances brain function and promotes socio-emotional and self-regulation skills (Yogman et al. 2018; Ginsburg 2007). Hsin and Felfe (2014) suggest that 'structured' leisure activities, such as playing sports with the child, in the USA are important activities in improving children's socio-emotional skills while 'unstructured' leisure, for example, watching television, are not. Certain kinds of play may help adolescents' skills development, but this relationship has rarely been explored in developing countries. It may be that having enough time for leisure reflects that an adolescent has autonomy over their time, positively associated with their self-efficacy, but there may also be 'too much' leisure time which reflects the opposite; that adolescents are idle without task-specific activities, negatively related to their self-efficacy.

Additionally, the displacement between the full range of these activities may matter. Rogoff (2003) argues that there may be a clash of values when education (often prescribed by 'Western' cultures) are introduced in cultures where contribution to the family is prioritised. In such environments, formal education may either be seen as a secondary activity that can only be pursued after the completion of immediately important tasks (e.g., working for the family), or families and adolescents can strategise to balance these activities. Often, the empirical literature on child labour treat adolescents' work and school attendance as strict substitutes. Edmonds (2008) argues that only using school and work indicators assumes that work is the only activity adolescents engage in besides school. Using UNICEF's Multiple Indicator Cluster Surveys (MICS) data, Edmonds (2008) shows that adolescents' work hours can increase up to a certain level with little effect on school attendance, demonstrating non-constant elasticity of substitution between work and school. Keane, Krutikova, and Neal (2020) further develops this issue using adolescents' full time budget from the YL data, focusing on cognitive skills. They find that domestic and economic work are not detrimental to adolescents' cognitive development if work only reduces time for leisure, but are detrimental if work reduces time for school. The authors further show that treating work and school as mutually exclusive activities overestimate the detrimental effects of child labour. My study will be the first to use methodology by Keane, Krutikova, and Neal (2020) to explain how different activities adolescents engage in may affect their socio-emotional skills, which may have different mechanisms to cognitive skills development.

2.3 Cross-country analyses

I examine these four countries which are in continents which as reported in ILO 2017, have high rates of child employment (Africa, the Americas, Asia, and the Pacific) which has an important bearing on how adolescents spend their daily time. However, Putnick and Bornstein (2015) study the relationship between child labour and school enrollment across 30 developing countries using MICS data and find that economic work outside the home only reduced the likelihood of school enrollment in 35% of the countries. The authors argue that the country differences show that there is no one universal policy intervention that easily explains adolescents time-allocation behaviours.

Analysing these countries provide four different settings to analyse the variations in relationships between adolescents' time use and their self-esteem and self-efficacy, where differences may be driven by social norms, labour market structures and education quality. Differences between countries can highlight the importance of local contexts to my findings, whilst similarities can show that individual-country findings are not unique and can feed into a wider global discussion. The country contexts also provide better nuance in understanding the gender and urban-rural differences in children's work and skills development.

Table 2.1 shows some national figures for each of the YL countries. While all four economies experienced high economic growth, poverty and income inequalities are still present. Ethiopia is the poorest country in the sample, a low-income country and one of the poorest in Africa. India, Peru and Vietnam are all classified as middle-income countries. Nearly a quarter of the population in Ethiopia is below the poverty line, a fifth in India and Peru and a tenth in Vietnam. Agriculture is an important sector for all YL countries except Peru, which instead has mining and manufacturing as its largest economic sectors. The importance of agriculture is reflected in the YL data where most of the adolescents sampled live in rural areas in Ethiopia, India and Vietnam and primarily work on the family farm, while adolescents in Peru are mostly urban.

Table 2.1: Illustrative national statistics in YL countries

Country	Agriculture as % of GDP	% of population below national poverty line	Primary NER (%)	Secondary NER (%)
Ethiopia	31	24	85	31
India	15	21	92	62
Peru	7	21	96	84
Vietnam	15	10	98	89

NER stands for net enrollment rate. Source for all statistics is World Bank (2018), except secondary NER in Vietnam. Secondary NER for Vietnam refers to lower secondary education (grades 6 to 9) in 2014, and upper secondary NER in Vietnam (grades 10 to 12) is 63.1% in 2014 (OECD 2017).

The official age for starting primary schooling is seven years old in Ethiopia and six in the other three countries. Compulsory education from primary school to the end of secondary school lasts for eight years in Ethiopia and India, and 10 years in Peru and Vietnam. Primary net enrollment rates (NER) – the percentage of students in the appropriate age group enrolled in primary education related to the total population of children of that age group – are highest in Peru and Vietnam and lowest in Ethiopia. While all secondary NER is lower, the rank is still the same; lowest in Ethiopia, followed by India, Vietnam and Peru. While each country has ratified international policy conventions against the worst forms of child labour, the topic is still a high-profile issue, and estimates from ILO (2018b) report that the highest estimates of child labour incidences are in these four continents: Africa, the Americas, Asia, and Oceania.

Studies about YL countries have shown that children and adolescents aged 5 to 17 in the sample in 2016 typically combine education and work. Ethiopian adolescents work the most; they work from the age of 5, at an equivalent average hour of work per day as 15-year-olds in the other four countries (Espinoza-Revollo and Porter 2018). Ethiopian adolescents also start primary school at a later age compared to the other countries (age 7 instead of age 6), and also enrol into school late; achieving their highest enrolment rates at age 12, reflecting poor access and attendance at primary schools. Ethiopian students also has the lowest achievement, measured by being at the appropriate grade for their age (grade-for-age), mathematics and verbal tests (Singh 2019).

In sharp contrast, Vietnamese students have the best academic performance out of the four countries, but also has the highest rates of school leavers by age 15 (Singh 2019). This movement is most apparent for boys (arguably, boys who do poorly in exams move into market work), and is reflective of national trends (Dang and Glewwe 2017).

While India and Peru are inbetween these two countries in terms of academic achievement and educational enrollment, Roest (2016) finds that at age 15, the transition to adulthood for girls and boys in India can be gendered, especially after the age of puberty. Girls in India who left school at 15-years-old were four times more likely to experience early marriage than girls who were enrolled at the same age. For boys, age 15 may be the time to consider entering market work early. Hossain and Jukes (2023) find that Ethiopia and India also have lower gender equal views among adolescents compared to Peru and Vietnam, and they find that these differences are associated with gender gaps in socio-emotional skills.

Lastly, adolescents in Ethiopia, India, and Vietnam are more likely to live in rural areas, compared to in Peru, where the majority of the sample live in urban areas. Espinoza-Revollo and Porter 2018 show that adolescents in rural areas work more than adolescents in urban areas. In examining the older cohort of adolescents in the YL sample, Favara, Chang, and Sánchez (2018) show that the majority of adolescents work by age 19 or 22, and this transition occurs earlier for boys than girls. The majority of adolescents work as dependent workers (usually paid), except for Ethiopia where self-employment is more prevalent (usually unpaid and self-sufficient).

To summarise more simply, I provide categorise these country-differences using four terminologies. While in all countries we can expect that more time in attending school or study is likely to be associated with improved self-esteem and self-efficacy, the associations from other activities are less clear. I term Ethiopian adolescents as 'work-oriented' as they work the youngest, start school the latest, and have large gender gaps in views. Hence, doing paid work may be considered 'usual' and may enhance self-esteem or self-efficacy as they are engaging in productive activities with adults and may help them secure self-employed work in the future. However, if gender roles are reversed i.e., boys do more unpaid work and girls do more market work, this may be associated with poorer self-esteem because of shame from expected gendered views. Since work is commonplace, more leisure time in place of work may be seen as idle, negatively associated with adolescents' self-esteem.

For Indian adolescents, I term them 'gender-biased and education-oriented' since they place strong emphasis on education enrollment but have large gender gaps in their transition to adulthood, with a bigger bias against girls. Here, unpaid work in place of education may be associated with worse self-efficacy for girls, since as mentioned in the previous sub-section, girls are confined to more domestic roles to conserve reputation, for their marriageable prospects. If domestic work comes at the cost of education, girls may be more affected than boys in India in relation to their self-efficacy.

For Vietnamese adolescents, I term them 'education achievement-oriented' since they are the highest achievers cognitively and academically of the four countries, but the trade-off of not performing well in school is punished by drop-outs of boys at age 15. Less time in school or study (and more time in paid or unpaid work) are likely associated with poorer self-esteem and self-efficacy, as they are seen as the most important pathways to a successful future.

The Peruvian adolescents compared to the other three countries are the most gender-neutral, with the exception that they are primarily in urban areas, which I will term as 'urban education-oriented'. Since urban types of work are likely safer and more manageable with time with education such as helping out in shops, there may be no significant associations between time at work and self-esteem or self-efficacy.

2.3.1 Returns to socio-emotional competencies in developing countries

Evidence about the returns to socio-emotional skills in developing countries are scarce, but growing. Studies find that socio-emotional skills are positively associated with successful labour market outcomes such as earnings and occupational attainment (Diaz, Arias, and Tudela 2013; Cunningham, Torrado, and Sarzosa 2016; Campos-Vazquez 2018; Bühler, Sharma, and Stein 2020; Ajayi et al. 2023; Yamada and Otchia 2022; Danon et al. 2023), and negatively associated with participation in risky behaviours (Mitchell et al. 2023).

Diaz, Arias, and Tudela (2013) and Cunningham, Torrado, and Sarzosa (2016) find that verbal and numeracy tests and perseverance or effort (grit) are positively correlated with earnings and labour market outcomes in Peru. Cunningham, Torrado, and Sarzosa (2016) however finds the results for socio-emotional skills vary depending on the skill measured; grit showed the strongest returns to labour market outcomes, but openness to experience and emotional stability is only correlated with employment. Campos-Vazquez (2018) find returns to the labour market in Mexico for both cognitive skills and locus of control, even after controlling for family background and educational attainment. Estimating the development of human capital in Peru using YL data, Mitchell et al. (2023) show that cognitive and socio-emotional skills (measured by agency, pride, self-esteem, self-efficacy, leadership skills, teamwork) are highly cross-productive. The authors also show how task-effectiveness, but not social skills, were strongly associated with lower young adult risk behaviours (e.g., taking drugs, excessive smoking and drinking) at age 22.

Across 17 African countries, Ajayi et al. (2023) find that socio-emotional skills are associated with higher earnings, especially interpersonal skills for women compared to men, but the achievement of interpersonal skills is lower for women, suggesting these skills are often under-represented. In examining garment-workers in Ethiopia, Yamada and Otchia (2022) find that task efficiency and confidence are particularly important types of socio-emotional skills for workers to be rewarded via written test performance and higher wages.

Lastly, using data from rural Thailand and Vietnam, Bühler, Sharma, and Stein (2020) find that Big Five personality traits, locus of control, risk, trust, and patience, play an important role in individuals' occupational attainment and earnings in rural labour markets. The authors highlight that conscientiousness in particular was associated with higher probability of being self-employed, while trust is an important determinant for individual earnings in most occupation types.

2.4 The Young Lives data

I use the YL survey, a longitudinal survey that tracks two cohorts of adolescents in four low and middle-income countries: Ethiopia, India (states of Telangana and Andhra Pradesh), Peru and Vietnam. The survey tracks the adolescents across 15 years with five rounds of data. I use data for the younger cohort (YC) who were born in 2001/2 and aged approximately one-year-old in Round 1, and five, eight, 12 and 15 years old in each consecutive round. There is a total initial sample of about 8,000 YC adolescents and families are followed-up with if they remained within the country.

Approximately 2,000 YC adolescents were randomly sampled by selecting 100 adolescents and households from each country's 20 sentinel sites/clusters. A sentinel site is a form of purposive sampling where the site or cluster is seen to represent a certain type of population, and is expected to show typical trends affecting the people of these areas. The older cohort (OC) were excluded because generalized self-esteem and self-efficacy scores were only administered at age 19 and 22, making the analysis of their time allocation complex because of transitions into adulthood and potential family formation. Although time use, and earlier scores of self-esteem and self-efficacy (agency and pride scores respectively) are available for YC and OC at ages 12 and 15, I do not do a cross-cohort comparison because agency scores in Rounds two and three were not internally consistent or reliable, as reported in Yorke and Portela (2018).

The sentinel sites selected represented each region, district or province in each country. The sentinel sites in Ethiopia, India and Vietnam were semi-purposively sampled to represent each country's socio-economic and geographic diversity, with a pro-poor bias. Peru instead adopted a random sampling of sentinel sites. The districts were ranked according to factors such as infant mortality, housing, schooling, and infrastructure. Excluding the top 5%, the districts were divided into equal population groups, ordered by a poverty index, and each district had a probability of being selected proportional to its population size.

The attrition rate between round one and five is low, with an average of 6.8%, or 0.5% per annum to compare to other longitudinal studies; 9.4% for Ethiopia, 5.5% for India, 9.4% for Peru and 3.1% for Vietnam. If deceased children are excluded from the calculation, the average attrition rates fall to 4.9%, equivalent to 0.3% a year; 5.4% in Ethiopia, 3.5% in India, 8.2% in Peru and 2.4% in Vietnam. (Sánchez and Escobal 2020). The reduction in attrition is especially large for Ethiopia, consistent with high infant mortality in Ethiopia during infancy compared to other stages of childhood, but there is no evidence of bias for the younger cohort. This attrition rate is the lowest compared to other longitudinal studies in developing countries such as Kenya Life Panel Survey (2.3% per annum), Mauritius Child Health Project (1.2% per annum), Birth to Twenty (BT20) in South Africa (1.8% per annum), Pelotas Birth Cohort in Brazil (1.8% per annum), and Cebu Longitudinal Health and Individual Nutrition Survey in the Philippines (1.3% per annum), among others (see Sánchez and Escobal (2020) for full list of studies and attrition rates).

Sánchez and Escobal (2020) also show that despite the low attrition, that attrition for YL is correlated with wealth, area of residence, ethnicity, and caste. In Ethiopia, India and Vietnam, families from urban areas and top terciles of wealth are more likely to attrit, whereas in Peru, rural households are more likely to attrit. The authors find that most of the bias is driven by wealth and area of residence and studies that control for this (as well as early household and caregiver socioeconomic characteristics) should limit the attrition bias, which I have taken into account in my analyses. The authors also suggest, as with other longitudinal studies, that using individual fixed effects estimates can be an alternative way to deal with potential attrition bias, which I also conduct in my analyses.

The YL data do not contain survey weights and are not designed to be nationally representative. However, studies by Kumra (2009), Escobal and Flores (2008), Outes-Leon and Sanchez (2008), and Nguyen (2008) show that in comparison to larger representative samples such as the Demographic Health Surveys, the YL samples cover a broad range of characteristics and attributes of the population, especially in the case for Peru. Initially, Escobal and Flores (2008) found that the sample for Peru in YL, after adjusting for the fact that each district had a probability of being selected proportional to its population size, there were no significant differences between the Young Lives and DHS samples, showing that analysis using the YL Peru sample resembles what is happening in the country. The strength of the YL data lies in its rich longitudinal data which contain information about the child and his/her household, and allows representative analysis of differences between groups (e.g. by sex and ethnicity) and across the child's life, in especially low-resource settings. The same time use and socio-emotional modules were administered in all four countries. Using four different countries allows me to examine common-trends or variations in this relationship in different settings.

2.4.1 YL Countries Background

Table 2.2: Average background characteristics of 15-year-olds in YL countries

	Ethiopia	**India**	**Peru**	**Vietnam**
Adolescent characteristics				
Female	0.47	0.45	0.49	0.48
Age in months	180.99	180.01	179.21	182.34
Height for age at age 5	-1.43	-1.62	-1.52	-1.33
Mathematics IRT score at age 12	415.39	465.25	508.46	580.93
Ethnicity				
Oromo (ET)/ Scheduled Caste (IN)	0.19	0.18		
Amhara (ET)/ Backward Caste (IN)/ Majority Kinh (VN)	0.29	0.46		0.87
Tigrian (ET)/ Scheduled Tribe (IN)	0.23	0.15		
Other ethnicity	0.29	0.20		0.13
Mother's main language is Spanish (for Peru only)			0.71	
Religion				
No religion	0.00	0.00	0.05	0.86
Christian	0.00	0.05	0.00	0.01
Muslim	0.17	0.07	0.00	0.00
Buddhist	0.00	0.01	0.00	0.07
Hindu	0.00	0.88	0.00	0.00
Catholic	0.01	0.00	0.81	0.00
Protestant	0.11	0.00	0.00	0.01
Orthodox	0.70	0.00	0.00	0.00
Evangelist	0.00	0.00	0.13	0.00
Mormon	0.00	0.00	0.00	0.00
Ancestor worship	0.00	0.00	0.00	0.04
Cao Dai	0.00	0.00	0.00	0.01
Other	0.01	0.00	0.00	0.00
Caregiver/parental characteristics				
Mother's age when adolescent was age 1	27.47	23.62	26.78	26.77
Caregiver's agency score, adolescent age 8	0.01	0.02	0.02	-0.00
Caregiver's pride score, adolescent age 8	0.02	0.01	0.02	0.01
Caregiver's education				
$\leq$ Incomplete primary education	0.79	0.79	0.36	0.36
Up to lower secondary	0.16	0.16	0.26	0.26
Up to upper secondary	0.00	0.00	0.24	0.24
Higher education	0.05	0.04	0.14	0.14
Household characteristics				
Adolescent is oldest in household	0.22	0.41	0.39	0.39
Number of siblings	4.01	1.61	2.63	2.63
Both parents in household	0.80	0.91	0.86	0.86
Household size	5.82	4.79	5.26	5.26
Household in urban location	0.36	0.30	0.75	0.75
Wealth index	0.42	0.64	0.63	0.63
Total observations	1551	1756	1698	1697

Note: The wealth index is a measure constructed and publicly archived by YL which is a simple average of housing quality, consumer durables, and access to services.

Table 2.2 describes the adolescents' background in each country. There is an even balance of girls and boys across all countries with similar ages. The majority caste in India is Backward Caste, and the majority ethnicity in Vietnam is Kinh. In Ethiopia, there is an even proportion of adolescents in three ethnic groups, Amhara (29%), Omoro (19%), and Tigrian (23%). In Peru, 70% of adolescents' mothers speak Spanish.

On average, mothers were 27 years old when the adolescent was one year old, except in India where the average mother is younger by four years. Family formation may be earlier for Indian women, which may have gendered consequences on how adolescents' time is allocated. Caregiver's education is much lower in Ethiopia and India than in Peru and Vietnam. In Ethiopia and India, about 80% of caregivers did not complete primary education. In Vietnam, the majority of caregivers have completed education up to lower secondary (56%), whilst in Peru about 26% of caregivers completed up to lower secondary and 24% completed up to upper secondary.[2]

Ethiopian adolescents have the most siblings on average, followed by Peru, India and Vietnam respectively. Ethiopian households are also the largest with an average of five – six people, compared to four–five people in the other three YL countries. While the majority of adolescents in each country have both parents in the household, this proportion is lower in Ethiopia and Peru (80% and 86% respectively). Most households live in rural areas except for Peruvian households which are primarily urban.

Using casewise deletion, the missingness are 14% in Ethiopia, 7% in India, 6% in Peru, and 10% in Vietnam. In examining the average characteristics of adolescents not included in the analyses (see Appendix Table A2.7), those excluded have are adolescents from less educated parents, less affluent families, and less healthy adolescents when they were 5 years old, in Ethiopia, India and Peru, but misses adolescents with parents up to lower secondary education and higher wealth indices in Vietnam. This implies that my main estimates may be excluding the most disadvantaged groups in Ethiopia, India, and Peru, but excludes more advantaged groups in Vietnam.

[2] In the full sample, at least 87% of caregivers are the adolescents' mother, and at least 90% of caregivers are the adolescent's biological parent.

2.4.2 Measures of self-esteem and self-efficacy

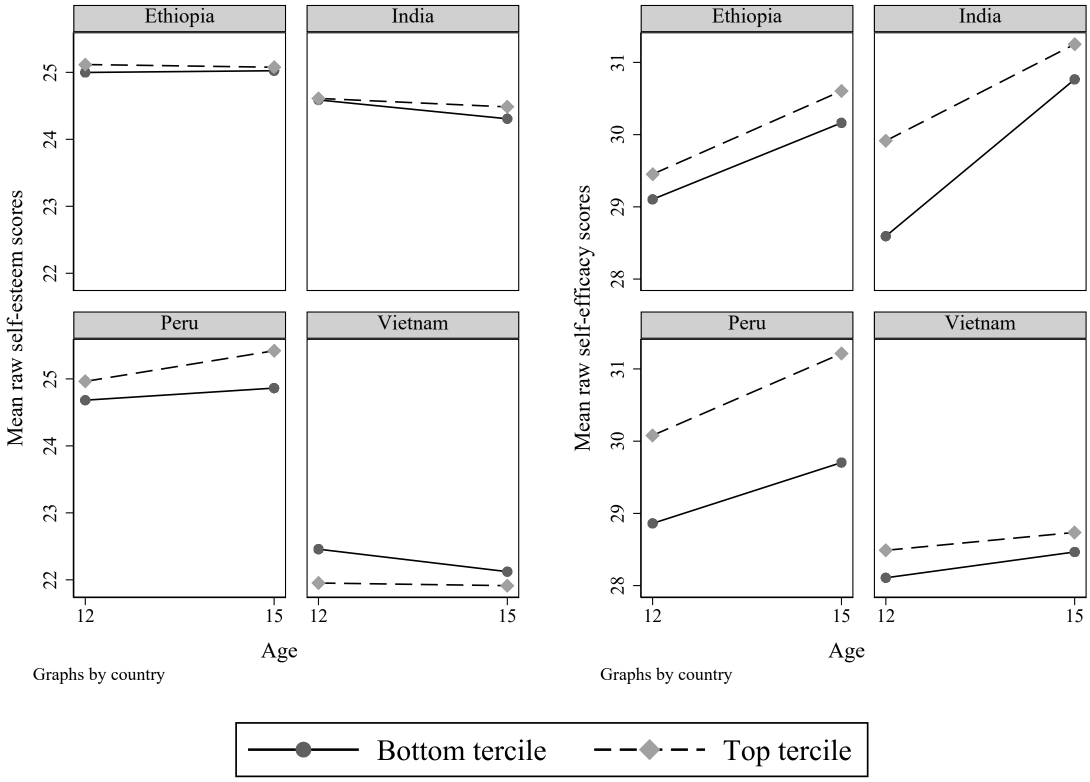
The two main social and emotional competencies of interest measured in the YL data are the generalised self-esteem and self-efficacy scores. The scores for each socio-emotional skill are made up of several Likert-type questions, ten questions for self-efficacy scores and eight questions for self-esteem scores, as detailed in Section 1 of the Supplementary Material.[3] The child responds to one of the five responses in each question, ranging from "strongly agree" to "strongly disagree". These same questions were administered in Rounds four and five, and across countries. A higher score implies greater generalised self-esteem or self-efficacy.

Self-esteem refers to an individual's judgement of their self-value and is measured using the Rosenberg self-esteem scale Rosenberg (1965). Self-efficacy is the measure of one's belief in his/her capabilities to produce expected results and to cope with adversity. Its scale was developed by Schwarzer and Jerusalem (1995). The scale is only administered in Rounds four and five because it was designed for adolescents above the age of 12. Note that in previous rounds, when the adolescent was 8 years old and below, agency and pride scores were used instead to measure social and emotional competencies of both the adolescent and their main caregiver. Agency is closely related to self-efficacy, measuring one's capability to exert influence over outcomes in one's life course. Pride is closely related to self-esteem, referring to an individuals' judgement of their own self-value or self-worth. As previously discussed, agency and pride scores were then replaced by the generalised self-esteem and self-efficacy as they better captured the adolescent's social and emotional competencies from age 12 onwards. Both self-esteem and self-efficacy scores are consistently used in psychology and economic studies in developed countries and are found to be positively associated with future economic outcomes in high-income countries (Heckman and Kautz 2013; Almlund et al. 2011; Heckman, Stixrud, and Urzua 2006). Studies by Luszczynska, Gutiérrez-Doña, and Schwarzer (2005) and Scholz et al. (2002) demonstrate that while country-differences exist, generalised self-efficacy is a consistent and universal construct tested across 25 and five countries respectively, with meaningful associations with

[3] All items are positively worded because reverse-coded items during the pilot performed poorly.

other personality constructs like self-esteem.

Figure 2.1: Wealth gradients of raw socio-emotional skills at age 12 and 15



Note: Raw socio-emotional skills by wealth terciles. The wealth index is a measure constructed and publicly archived by YL, which is a simple average of housing quality, consumer durables, and access to services.

Yorke and Portela (2018) demonstrate that both these generalised scales are consistently measured at age 12 in the four YL countries. At age 15, Appendix A Table A2.2 to Table A2.5 report that the average inter-item correlations fall between the recommended range of 0.15 and 0.50 (Clark and Watson 1995), and the alpha scores of reliability are close to the threshold of 0.7.

To examine descriptively how self-esteem and self-efficacy change across time, Figure 2.1 reports how the raw self-esteem and self-efficacy score may change by age, and between high and low wealth terciles. Previous studies in developing countries have shown that there are typically wealth gaps across skills, since more advantaged parents can invest in their children (Attanasio, Meghir, and Nix 2020). Therefore, we should expect to see that scores increase across time, especially for those from high wealth terciles. In addition, if these scores increase across time, it also validates the use of VA models which use previous skills as a proxy of unobserved characteristics for future skills. For self-efficacy, there is an overall increase in scores between the ages 12 and 15, suggesting that skills accumulate across time. The average self-esteem scores however, remain somewhat similar across age groups with little wealth gaps, which may explain why we see greater significant associations in self-efficacy scores.

I standardise the generalised self-esteem and self-efficacy scores separately by country, with a mean zero and standard deviation of one to measure the changes in scores more intuitively. In Appendix A, tables A2.2 to A2.5 show the cronbach alpha's and item-test correlations across the four countries. TableA2.6 shows the distribution of the standardised scores in each country and age. While the socio-emotional questions were administered in the same way across all YL countries, I cannot account for different local norms or interpretations of the questions. Therefore, I compare common trends across the countries, not ranking their scores against each other.

2.4.3 Adolescents' time allocation on a typical day

To measure time allocation, the adolescents were first asked to think of the most recent typical week (excluding festivities), and then to think of a typical day. A typical day is defined as a weekday or a normal school day that excludes days of rests, such as holidays, festivals and the weekend. The adolescents are then provided 24 pebbles/beans which represent 24 hours in a day, and asked to allocate them into eight cups/circles that illustrate eight different activities on a typical day in the past week. The adolescents are first required to allocate hours into sleep, and then asked to distribute the pebbles/beans among the remaining seven activities; leisure, time spent in school, time spent studying outside school, domestic chores, care work, work for the household, and paid work outside the household. Since sleep has little variation in the data, I exclude interpreting estimates of sleep in my analysis.

I group household tasks and paid work outside the household broadly as 'economic work', as both encompass similar types of tasks, and less than 10% of adolescents perform paid work outside the household. I also group care work and household chores as 'domestic work'. I am unable to further break down leisure, as it is broadly categorized in the data. In my analysis, I use five activity categories as described in Table 3 below, observed at ages 12 and 15.

Table 2.3: Time use description in the Young Lives data

Activity	Description
Economic work	*Household tasks*: Work inside the household which generates income; this includes farming, cattle herding, shepherding, piecework or handicrafts done at home and other family businesses *Paid work outside household*: Paid (remunerated) work or activities outside of the household or for someone not in the household including (if applicable) travel time to and from work
Domestic work	*Care work*: Taking care of other household members, such as younger siblings, elderly, or members with disabilities within the household *Household chores*: Work or task done to help at home e.g. fetching water, firewood, cleaning, cooking, washing, shopping and so on; excludes caring for others
At school	Time spent at school including time used to get from home to school and from school to home
Studying outside school	Time child spends studying at home and doing homework or attending classes or tutorials outside school class hours
Leisure	Time child spends playing or having fun, having meals, bathing and so on
Sleeping	Includes time when child takes a nap

Note: Definitions are taken from YL Briones (2018), complemented with further information on each activity from the YL fieldworker manuals. Domestic work refers to work done within the child's household only.

2.4.4 Control variables

There may be several individual-level, caregiver-level, and household-level characteristics which are important in explaining the associations between time use and self-esteem and self-efficacy. At the individual-level, I control for adolescent's age, sex, religion, and ethnicity/caste, all of which may influence how they spend their time. Biological components which may influence the adolescent's social and emotional development because of brain development, is controlled for using height-for-age z-score at age five. I also control for their cognitive score, measured by their mathematics score, since cognitive scores and social and emotional competencies are positively correlated.

At the caregiver-level, I control for mother's age when the adolescent was born because older mothers are more likely to be more financially stable (in a longer marriage) compared to younger mothers, especially in the case of India. Caregiver's education is important as it may determine how much caregivers value education and hence, whether they are more likely to allocate the adolescent's time towards or away from education. Education also proxies for socioeconomic status, which determines how much the caregiver requires the adolescent's time to perhaps substitute for their own time, or to complement time in economic activities. An additional socio-economic peoxy are wealth terciles, which is a simple average of housing quality, consumer durables, and access to services as they are a more accurate measure of wealth compared to using income, especially in deprived areas. I also include the caregiver's pride and agency scores (early measures of self-esteem and self-efficacy respectively) when the adolescent was eight years old which provides a proxy for a caregiver's influence on the adolescent's skills through upbringing.

At the household-level, I include household size, whether the adolescent is the older sibling, and number of siblings as studies have shown that birth order and household size (especially in relation to the number of siblings), is associated with adolescents' participation in economic work (Seid and Gurmu 2015). Whether or not both parents live in the household proxies again for financial stability, and hence the adolescent's likelihood of attending school or doing economic work. Lastly, I control for urban/rural locality of the household, as adolescents in rural households are more likely to be engaged in some form of work compared to urban households.

2.5 How YL adolescents spend their time on a typical day

Table 2.4 reports engagement in activities, while Table 2.5 reports the average hours spent in each activity including those who do not perform the activity (unconditionally), and if they perform the activity (conditionally). Adolescents typically combine some form of educational activity and domestic work. Division of labor by sex is evident; more girls participate and spend more time in domestic work while more boys engage in economic work. The gender gap is most pronounced in India. Section 3 of the Supplementary Material demonstrate leisure time falls while time in work increases between the ages five to 15. Time at school and for study rises slowly across age. At age 5, adolescents in Ethiopia spend the most unconditional hours in domestic work, and the least unconditional hours attending school compared to the other three countries. In the other three countries, the most prominent rise in unconditional hours in work, primarily domestic work, is seen at age 12.

The majority of adolescents engage in educational activities: 84% to 96% of adolescents attend school and 81% to 96% study outside school. The hours in school reflect the average country school lengths of six–eight hours a day in India, six hours a day for Ethiopia and Peru, and nine hours in Vietnam including co-curricular activities (seven hours excluding co-curricular activities). The average commuting time is approximately one hour to and from school. In all YL countries except Peru, more girls engage in attending school as well as studying outside school, but with little difference in hours spent in these activities.

The typical work adolescents engage in all four countries is domestic work. However, those involved in economic work spend more hours in it compared to domestic work, primarily from helping in their family household tasks. Since I lack disaggregated information on types of work, qualitative YL research shows that most adolescent' economic work in rural areas is related to agriculture such as herding livestock, harvesting, and stone crushing Morrow and Boyden (2018). In Peru, Cussianovich and Rojas (2014) describe urban adolescents' work as mirroring their parents' economic activity, usually in informal trade such as selling flowers or food on the street, or as a vendor.

Table 2.4: Prevalence of children engaged in activity, age 15

Percentage of children in activity (%)	Ethiopia				India				Peru				Vietnam			
	Total	Girls	Boys	Diff (boys-girls)	Total	Girls	Boys	Diff (boys-girls)	Total	Girls	Boys	Diff (boys-girls)	Total	Girls	Boys	Diff (boys-girls)
In school	93.6	95.5	91.9	-3.6***	90.1	88.5	91.5	3.1**	95.6	96.3	95.0	-1.3	83.5	87.7	79.6	-8.1***
Studying outside school	90.5	93.2	88.1	-5.1***	87.7	87.8	87.6	-0.3	95.5	96.3	94.8	-1.5	80.7	86.4	75.4	-10.9***
Any form of work	97.6	99.2	96.2	-2.9***	77.7	81.2	74.8	-6.4***	89.0	89.6	88.5	-1.2	90.1	91.4	89.0	-2.3
Domestic work	91.3	98.5	84.8	-13.7***	76.4	80.7	72.9	-7.8***	87.2	88.7	85.8	-2.9*	86.4	88.9	84.0	-4.9***
Economic work	48.7	33.6	62.5	28.9***	12.9	8.6	16.4	7.7***	18.2	15.5	20.8	5.3***	35.7	31.4	39.7	8.3***
Play/leisure	98.5	98.5	98.4	-0.1	99.5	99.7	99.4	-0.38	99.8	99.8	99.8	0.0	100.0	100.0	100.0	0.0
Sleep	100.0	100.0	100.0	0.0	100.0	100.0	100.0	0.0	100.0	100.0	100.0	0.0	100.0	100.0	100.0	0.0
Total Observations	1551	736	815		1756	798	958		1698	839	859		1695	821	874	

Note: Domestic work includes household chores and care work. Economic work includes work for pay outside the household and household tasks.

Table 2.5: Unconditional and conditional hours in activities, age 15

	Ethiopia					India					Peru					Vietnam				
	Total	Min	Max	95% CI	Gender gap (boys-girls)	Total	Min	Max	95% CI	Gender gap (boys-girls)	Total	Min	Max	95% CI	Gender gap (boys-girls)	Total	Min	Max	95% CI	Gender gap (boys-girls)
Unconditional average hours spent in activity (including those not performing activities)																				
In school*	5.5	0.0	11.0	[5.3, 5.5]	-0.3***	8.0	0.0	14.0	[7.9, 8.1]	0.3**	6.9	0.0	12.0	[6.8, 7.0]	-0.2*	5.2	0.0	11.0	[5.1, 5.4]	-0.5***
Studying outside school	1.9	0.0	8.0	[1.9, 2.0]	-0.1**	2.1	0.0	8.0	[2.1, 2.2]	-0.1**	2.1	0.0	9.0	[2.0, 2.1]	-0.2***	2.6	0.0	10.0	[2.6, 2.7]	-0.7***
Any form of work	4.5	0.0	16.0	[4.4, 4.6]	0.07	2.1	0.0	17.0	[2.2, 2.3]	-0.4***	2.5	0.0	16.0	[2.4, 2.6]	0.0	3.0	0.0	16.0	[2.8, 3.1]	-0.02
Domestic work	2.7	0.0	13.0	[2.6, 2.8]	-1.7***	1.3	0.0	10.0	[1.9, 2.2]	-0.5***	2.0	0.0	16.0	[1.9, 2.1]	-0.3***	1.7	0.0	11.0	[1.6, 1.8]	-0.3***
Economic work	1.8	0.0	15.0	[1.6, 1.9]	1.7***	0.7	0.0	13.0	[0.6, 0.8]	0.1	0.5	0.0	14.0	[0.4, 0.6]	0.3***	1.3	0.0	15.0	[1.1, 1.4]	0.3**
Play/leisure	3.3	0.0	14.0	[3.3, 3.4]	0.2**	3.5	0.0	15.0	[3.5, 3.6]	0.1	3.4	0.0	12.0	[3.4, 3.5]	0.2**	4.6	1.0	16.0	[4.5, 4.8]	0.9***
Sleep	8.8	5.0	14.0	[8.8, 8.9]	0.1**	8.3	5.0	12.0	[8.2, 8.3]	0.1**	8.7	4.0	14.0	[8.6, 8.7]	0.1**	8.5	4.0	18.0	[8.4, 8.5]	0.2***
Conditional average hours spent in activity (if activity performed)																				
In school*	5.8	2.0	11.0	[5.8, 5.9]	-0.1**	8.9	5.0	14.0	[8.8, 8.9]	0.0	7.2	2.0	12.0	[7.2, 7.3]	-0.1	6.3	0.0	11.0	[6.2, 6.3]	0.0
Commute (to and from school)	1.1	1.0	4.0	[1.1, 1.1]	0.0	1.1	1.0	8.0	[1.1, 1.2]	0.0	1.2	1.0	8.0	[1.1, 1.2]	0.0	1.1	1.0	4.0	[1.0, 1.1]	0.0
Studying outside school	2.1	1.0	8.0	[2.1, 2.2]	0.0	2.5	1.0	8.0	[2.4, 2.5]	-0.1**	2.2	1.0	9.0	[2.1, 2.2]	-0.2***	3.3	0.0	10.0	[3.2, 3.4]	-0.4***
Any form of work	4.6	1.0	16.0	[4.5, 4.7]	0.2*	2.6	1.0	17.0	[2.5, 2.8]	-0.3	2.8	1.0	16.0	[2.7, 2.9]	0.0	3.3	0.0	16.0	[3.1, 3.4]	0.1
Domestic work	3.0	1.0	13.0	[2.9, 3.1]	-1.3***	1.7	1.0	10.0	[1.7, 1.8]	-0.5***	2.3	1.0	16.0	[2.2, 2.4]	-0.3***	2.0	0.0	12.0	[1.9, 2.0]	-0.2***
Economic work	3.6	1.0	15.0	[3.4, 3.8]	1.6***	5.6	1.0	13.0	[5.1, 6.1]	-2.6***	2.9	1.0	14.0	[2.7, 3.2]	0.7**	3.5	0.0	15.0	[3.3, 3.8]	0.0
Play/leisure	3.4	1.0	14.0	[3.3, 3.5]	0.2**	3.5	1.0	15.0	[3.5, 3.6]	0.1	3.5	1.0	12.0	[3.4, 3.5]	0.2**	4.6	1.0	16.0	[4.5, 4.8]	0.9***
Sleep	8.8	5.0	14.0	[8.8, 8.9]	0.1**	8.3	5.0	12.0	[8.2, 8.3]	0.1**	8.7	4.0	14.0	[8.6, 8.7]	0.1**	8.5	4.0	18.0	[8.4, 8.5]	0.2***
Total Observations				1551					1756					1698					1695	

Note: *In school refers to time spent in school, including time spent commuting to and from school.

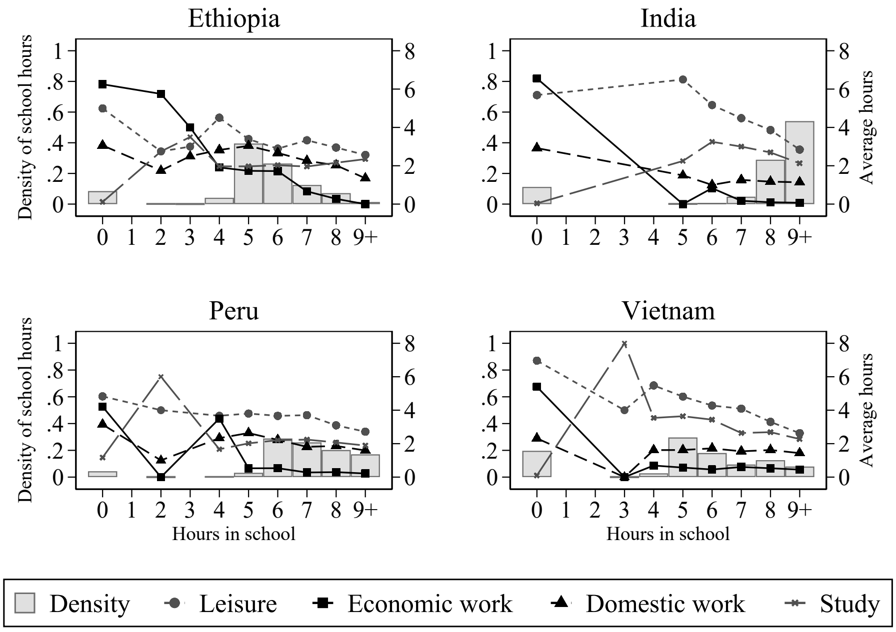
Ethiopia has the highest percentage of adolescents involved in domestic or economic work, nearly double that to the percentage of adolescents in India and Peru. Of those involved in domestic work, Ethiopian adolescents also spend the most hours on it (4.6 hours on average). Ethiopian adolescents' time is more evenly spread between each activity, implying lower elasticities of substitution. In the other three countries, adolescents are mainly engaging in domestic work and educational activities. Adolescents in India engage the least in economic work (13%), but those who do spend an average of 5.6 hours in this work, the highest of all four countries. This suggests a large trade-off between economic work and school. Morrow and Boyden (2018) describe how in times of difficulty, boys in India were expected to work to contribute to family finances.

2.5.1 Trade-offs between activities on a typical day

With only 24 hours in a day, investing more hours in one activity means less for another. Figures 2.2 to 2.4 plot the average hours spent in an activity on the right y-axis against hourly increases of a base activity across the x-axis. Densities of the baseline activity are reported on the left y-axis. For example, Figure 2 uses school attendance as the baseline category. The top left chart shows that adolescents in Ethiopia who mostly spend five hours in school (base category) spend on average 3 hours in domestic work and leisure and two hours in economic work.

Changing the counterfactual category in these figures show us different snapshots of how adolescents' time is divided. Figure 2.2 shows us the difference between adolescents who attend school and those who do not, with some variation in the average hours of school attendance. At zero school attendance, adolescents in all four countries spend on average between four and seven hours in economic work and leisure respectively, and about half that in domestic work. When adolescents spend an average number of hours in school (the highest density), less time is spent in leisure. Additionally, in all countries except Ethiopia, economic work time falls to near zero. However, time devoted to domestic chores remains similar at two–three hours. Adolescents who report spending more than nine hours in school do not participate in economic work, but still spend an average of one–two hours in domestic work, indicating that domestic work is a persistent work activity even among adolescents with greater hours of educational activities.

Figure 2.2: Average hours in play and work against average hours in school activities

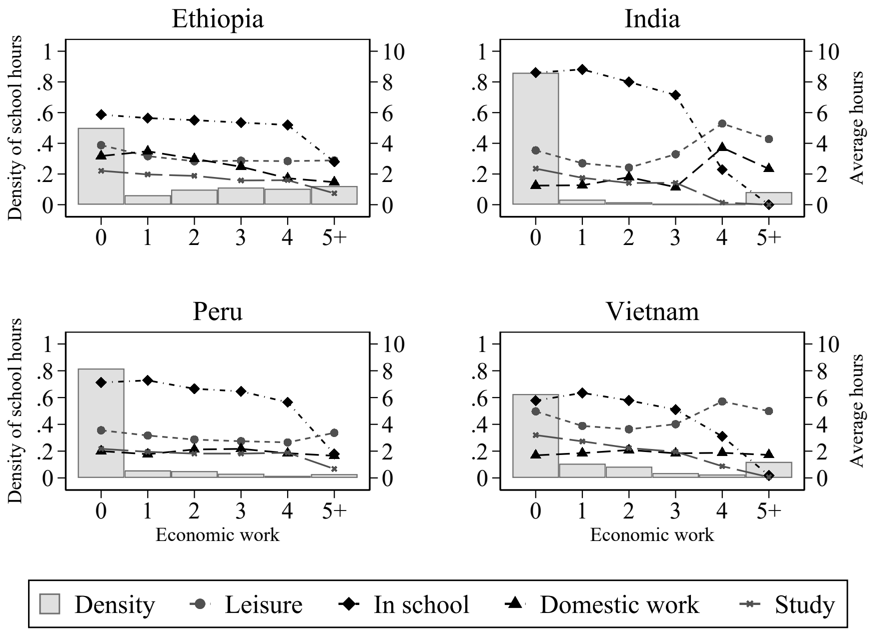


Note: Densities reported are densities of the baseline activity. Domestic work groups together household chores and care work. Economic work groups together household tasks and paid work outside the household. Sleep is excluded.

Figures 2.3 and 2.4 meanwhile, show how adolescents divide their time conditioned on time spent in economic or domestic work. Although few in number, adolescents who do more than five hours of domestic and/or economic work show a rise in leisure time in India and Vietnam, but not in Ethiopia and Peru. On the one hand, adolescents engaging in economic work may prioritise leisure, taking time away from education (e.g. India). On the other hand, leisure may be sacrificed, to maintain similar levels of education and work (e.g. Ethiopia). How activities are divided in a day are important and differ according to the conditional activity.

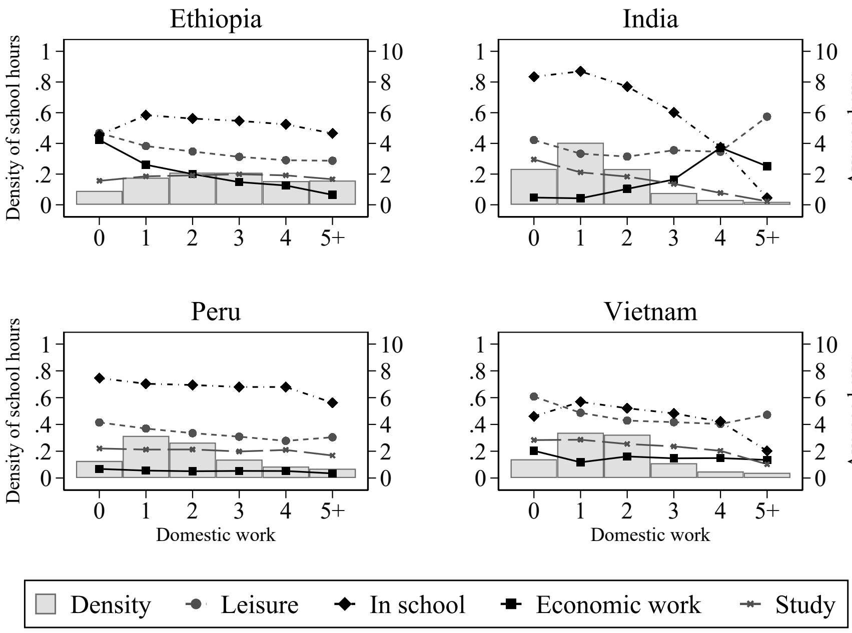
Elasticities of substitution between work and educational activities appear to be largest in India. For example in Figure 2.4 for India, adolescents who spend 3 hours in domestic work compared to 1 hour in domestic work spend about 2 hours less in school, and 0.5 hours less in studying outside school. Compare this to Ethiopia where the same change show adolescents spending 0.3 less hours in school and nearly no difference in study time.

Figure 2.3: Average hours spent in activities conditional on economic work as baseline activity



Note: See note in Figure 2.2 above for details.

Figure 2.4: Average hours spent in activities conditional on domestic work as baseline activity



Note: See note in Figure 2.2 above for details.

2.6 Empirical framework to model self-esteem and self-efficacy formation

I use extended VA models to evaluate how adolescents' time spent in an additional hour of an activity, compared to a counterfactual activity, is associated to their self-esteem and self-efficacy. VA models are widely used in the literature on adolescent skills formation (Fiorini and Keane 2014; Del Boca, Monfardini, and Nicoletti 2017; Cunha and Heckman 2008; Todd and Wolpin 2007) to reflect decisions made in the adolescents' life up until the observed point, and hinge on the identifying assumption that lagged skills capture the contribution of all previous observed, unobservable inputs, and adolescent's ability. Lagged skills are assumed to be sufficient proxies if the *effects* of all past time-varying inputs (observed, unobserved and ability) on adolescents' current self-esteem or self-efficacy decline at a constant rate across time, from the time the input was applied. For example, farm work at age eight has a larger effect on skills at age eight than at age 15. To relax this assumption, I include time inputs at age 12, instead of assuming a constant rate of decline between ages 12 and 15.

For each adolescent in each household in each country, I estimate:

$$S_{15} = \alpha + \gamma S_{12} + \delta M_{12} + \beta T_{15} + \pi T_{12} + \sigma X_{15} + \rho C_{15} + \varepsilon \qquad (2.1)$$

where S_{15} is the adolescent's measured skill score at age 15 i.e. generalised self-esteem and self-efficacy scores. S_{12} is the adolescent's lagged skill score, and M_{12} is the lagged cognitive (mathematics) score. T_{15} and T_{12} are the vectors of hours spent in the five different activities described in Table 2.3 at ages 15 and 12 respectively. My coefficient of interest is β which measures the effect of an additional hour spent in an activity of interest compared to a counterfactual activity on the adolescent's skill at age 15. To examine the shifts between different activities, I re-estimate the same model but use different counterfactual activities and re-examine the β coefficient estimates.

X_{15} are measures of observed adolescent, caregiver and household-level background characteristics, as discussed in 2.4.4. To control for potential seasonal effects, I control for month of interview indicators. Since YL data adopts semi-random sampling of sentinel sites, adolescents within sentinel sites are likely to have similar access to local labour markets, education and health infrastructure. Therefore, I include country-specific cluster fixed effects at age 15, C_{15}, and cluster all standard errors at the sentinel site level. I also estimate model (2.1) separately for girls and boys to examine differences by sex.

The model relies on assumptions for causal interpretation of the estimates, potentially challenged by two sources of endogeneity. First, the presence of unobservables that affect both the adolescents' skill formation and parental investments. For example, the adolescent's unobserved confidence which may be positively correlated with the caregiver's perceived returns from economic work and the adolescent's self-esteem or self-efficacy. If caregivers of confident adolescents prefer them to work in the family business rather than attending school, then an ordinary least squares (OLS) estimation of my baseline would overestimate the actual impact from an additional hour in economic work, and vice versa if caregivers favour school attendance. Depending on the correlation between the unobservables, time allocation and skill scores, OLS estimates of β could be biased upwards or downwards. A second source of endogeneity is through reverse causality i.e. the caregiver may observe the adolescent's prior skills and consequently adjust the adolescent's time spent in work, school or leisure, T_{15}, again leading to inconsistent estimates using OLS.

2.6.1 Multiple hypotheses testing and fixed effects

I am fitting models for two outcome variables (self-esteem and self-efficacy), and five time inputs (domestic work, economic work, leisure, attending and sleep in contrast to a reference activity, e.g. studying outside school) for each YL country. This results in 10 p-values for each country. Since each country sample is independent of the other's, the main concern for multiple comparisons are those made within a country. Examining more than one outcome variable may increase risks in making a Type I error (claiming statistical significance when there is in fact, no relationship) when interpreting the 10 p-values within each country. To allay such concerns, I derived Romano-wolf p-values for all my cumulative model estimates, based on 100 replications.

Studies such as by Caetano, Kinsler, and Teng (2019) demonstrate that using a rich set of controls, lagged scores and the full set of adolescents' activities absorb endogeneity from omitted variables and measurement error in VA models (see Section 1.7 in Chapter 1). However, as discussed previously, the VA model relies on strict assumptions that the effects of unobservable inputs and latent ability on self-esteem and self-efficacy are declining across age at the same rate and thus lagged scores controls for these unobservables. It may be that this assumption is not reasonable, and instead that the effects of unobservable inputs and latent ability are constant across time. If this is true, then differencing or de-meaning eliminates them. Using this technique means that the model shows that within-person variation across time, and removes the differences between persons. This can be done using fixed effects estimations which removes time-invariant unobservables, but has the limitation that it does not allow for estimating time-variant determinants. Large differences between the fixed effects estimates and the VA estimates would suggest that my results are vulnerable to the way unobserved ability is controlled for, while similar estimates will provide more confidence to my main findings.

2.7 Results

2.7.1 Main specification

Figures 2.5 and 2.6 show how adolescents' time spent relative to a baseline activity is associated with their self-esteem and self-efficacy. In each figure, there are a total of six activities, and one is used as a baseline activity. Each figure has a different baseline activity; attending school in Figure 5, and leisure in Figure 6. Omitting different baseline activities show how each of the five activities are associated to adolescents' skills relative to the omitted activity, but uses the same model.

There are two plots in each figure, one for each indicator. The coefficient estimates are interpreted as the association from an additional hour spent in the specified activity on the vertical axis, relative to the baseline activity. The horizontal axis is the scale of the coefficient estimate in standard deviations (SD) away from zero. Appendix C show the corresponding full regression estimates, demonstrating that estimates with or without lagged time inputs (age 12) are largely similar, and Appendix D shows that the narratives are similar after multiple hypotheses testing.[4]. The coefficient plot using studying outside school as an omitted category is not shown here as estimates are less precise.[5]

Figure 2.5 shows that an additional hour of domestic work instead of attending school reduces adolescents' self-efficacy in all countries except Peru, all else constant. In Ethiopia and India, an additional hour of domestic work is associated with -0.03SD and -0.04SD of self-efficacy respectively. However, the magnitude of the estimates for Peru and Vietnam are small and close to zero (-0.01 SD). The associations are also statistically significant for self-esteem, but only in Ethiopia (-0.04SD). Figure 2.6 shows that when omitting leisure instead, the estimates are smaller in magnitude and are weakly significant.

Estimates show that economic work is only detrimental for adolescents in India, if it comes at the cost of school. While this is expected for Ethiopia being 'work-oriented', it is a bit more surprising for Peru and Vietnam. For Peru and Vietnam, regardless of the omitted activity, domestic or economic work produces near zero estimates and are insignificant. The sample of adolescents in Peru are primarily urban while the other three are more rural. A potential explanation is that adolescents in urban settings may have access to better quality education or work that is better balanced with attending school. For example, working in a family shop is less labor intensive than a family farm. It may be also explained by the elasticities of substitution seen in Figure 2.4 previously; incidence of economic work is low in Peru and Vietnam, and few adolescents do more economic work despite spending less time in other activities, e.g., Vietnamese adolescents substitute towards more leisure time instead.

Generally, leisure is neither more nor less productive than work activities in any of the countries, or related to worse self-efficacy if it comes at the cost of domestic work in Ethiopia and India. The magnitude for self-efficacy in India is smaller (-0.02SD instead of -0.04SD), and the estimates are only statistically significant at the 1% level. Recall that leisure

[4]The exception is that study that displaces leisure is statistically significantly associated with 0.01SD of self-efficacy in Vietnam

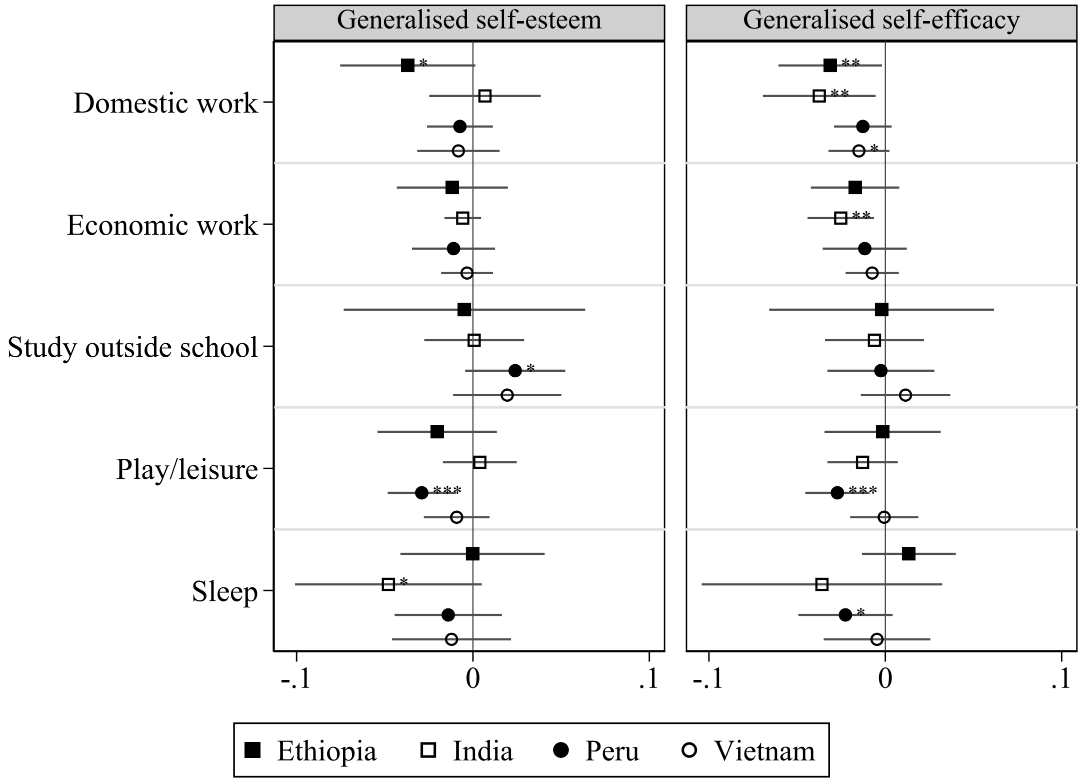
[5]Estimates for a latent model of socio-emotional skills is estimated and reported in Appendix E.

measured in the YL data is a broad set of activities including playing, personal hygiene and eating. This measure could be capturing 'unstructured' leisure time or 'idle' time which according to Hsin and Felfe (2014) is unproductive for adolescents' skills development. Dedicated, structured play time could instead be captured by time spent in other activities such as domestic work and/or studying outside school. Controlling for the type of school shows that estimates remain robust (see Appendix F). In Peru, there is a consistent negative association on self-esteem and self-efficacy from an hour of leisure instead of school (-0.03SD). This may be due to the introduction of the Jornada Escolar Completa (JEC) program in Peru in 2015. The program's aim was to increase the quality of secondary school education, and extended the school day by two hours. Leisure that replaces time for this improved educational activity could have been associated with poorer self-esteem and self-efficacy.

In line with this, we also see the converse where in Peru, attending school or studying outside school that reduces leisure time improves both self-esteem and self-efficacy, statistically significant at the 1% level (0.03SD and 0.04SD respectively). These estimates for the other three countries are close to zero or weakly significant. While this is expected in Peru being 'urban education-oriented', similar estimates are not seen for Vietnam 'education achievement-oriented' and India 'gender biased and education-oriented'. It may be that the introduction of an extended school day (with targeted activities in school) could have improved adolescents' contact with good role models and peers, improving their self-esteem and self-efficacy. Notably, more time studying instead of school or leisure is also associated with improved self-esteem in Peru (0.02SD and 0.04SD respectively). It may be that extra classes in Peru are viewed to be prestigious, as the extension of the school day could improve families' and adolescents' views about education.

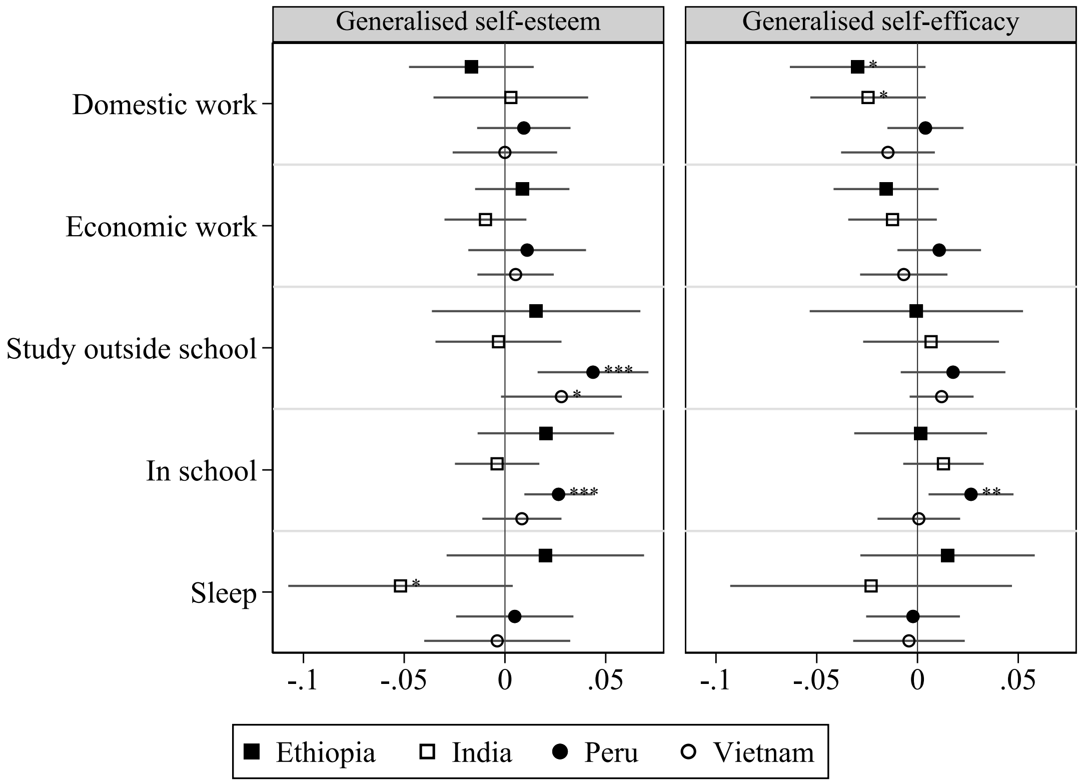
The fixed effects estimations in Appendix G which assume that the effects of unobservables are time-invariant show a similar narrative whereby domestic work and leisure are unproductive inputs, and attending school is productive. The exception is that in contrast to the main estimates where I did not find statistically significant associations, an additional hour studying outside school instead of attending school, every round, is associated with poorer self-esteem for Ethiopian children, and poorer self-efficacy for Indian children. This may indicate that the VA model is under-estimating the associations between study and social and emotional competencies in these two countries particularly. Overall, it is re-assuring that the main VA estimates are largely similar to the fixed effect estimates despite different assumptions, giving added confidence that the main estimates remain robust.

Figure 2.5: Coefficient estimates of time use on self-esteem and self-efficacy age 15, **attending school** omitted



Note: The coefficient plots show the coefficient estimates for generalised self-esteem in the left chart and for generalised self-efficacy in the right. Estimates for each YL country are plotted from model (2.1), controlling for adolescent, household and parental controls, generalised self-esteem or self-efficacy scores at age 12, and time use activities at age 12. The vertical line in each chart indicates an estimate of zero. The estimates are interpreted as an additional hour in each of the activity categories; domestic work, economic work, studying outside school, leisure and sleep; instead of attending school. To the left of the vertical line, an additional hour in the activity of interest instead of attending school reduces the respective socio-emotional skill, while to the right indicates an increase in the respective socio-emotional skill. Plots show 95% confidence intervals. Standard errors are clustered at the cluster-level. p-values are indicated by ** p<0.05, *** p<0.01.

Figure 2.6: Coefficient estimates of time use on socio-emotional skills age 15, with **leisure** omitted



Note: See Figure 2.5, but estimates are interpreted as an additional hour in each activity instead of leisure.

2.7.2 Linearity in the relationship

The detrimental associations of work or leisure on self-esteem or self-efficacy may be non-linear i.e., more detrimental with high hours of work or leisure due to excessive stress or idle time. To examine these non-linearities, I re-run my baseline model with the squared hours in leisure, domestic work, and economic work. Firstly, not reported here, I do not find any statistically significant increases in detrimental associations between leisure and adolescents' self-esteem nor self-efficacy in all countries, suggesting a linear relationship.

Secondly, Appendix H reports the estimates including squared terms for domestic and economic work. There are no statistically significant non-linear associations between work hours and self-esteem or self-efficacy, except for Ethiopia and Vietnam. Even if statistically significant, magnitudes of the squared terms are close to zero. Using Vietnam as an example, an additional hour of work from zero hours of economic work instead of attending school reduces generalized self-efficacy by 0.05 standard deviations, holding all else constant. Each additional hour of economic work increases the slope of this association by 0.005 standard deviations up to a turning point (about five–six hours). However, from two hours of work, confidence intervals become very large, and non-linearities are imprecisely estimated. In sum, estimates are linear, or non-linear associations are small.

2.7.3 Heterogeneity by sex and location

Tables 2.6 and 2.7 show differences in work relationships to skills by sex. Much like the baseline estimates, self-efficacy is most negatively associated with domestic work. Table 2.6 shows that domestic work harms girls' self-efficacy more than boys in all countries. When school is omitted, the estimates are significant in all countries except Ethiopia, but magnitudes are much larger and more negative for girls in Peru and Vietnam (0.03SD for girls compared to near zero for boys). This shows that unlike the hypothesised country-mechanisms that only Ethiopia and India are likely to have gendered gaps, all countries exhibit a female-bias in terms of the negative associations of domestic work. More time in economic work instead of school is significantly associated with poorer self-efficacy for both girls and boys in India (-0.02SD), and for girls in Vietnam (-0.02SD), and the negative associations of work instead of school is larger for girls than boys across all countries. While the coefficient sizes seem larger for domestic work compared to economic work, an F-test cannot reject the null that the coefficient estimates between these types of work are different. When leisure is omitted, there is little evidence of sex differences in work activities.

For Ethiopia, more time in economic work instead of leisure or school have larger negative associations for girls' self-efficacy than boys (-0.04SD instead of -0.02SD). Boys who do an additional hour of domestic work instead of attending school have significantly lower self-esteem than girls (-0.06SD), and this estimate is significantly different to the magnitude of economic work. This is in line with previous work by Boyden, Porter, and Zharkevich (2021), indicating that boys or girls doing their opposing 'gender roles' have lower self-esteem, but my estimates also show lower self-efficacy for girls.

Leisure time that reduces school time reduces girls' self-esteem more than for boys in Peru and Vietnam, but the opposite is true for boys in Ethiopia. When leisure is omitted, the significant associations of educational activities on Peruvian adolescents' self-esteem and self-efficacy are mainly driven by girls, showing that girls stand to gain the most from more educational activities in Peru.

As previously discussed, urban and rural localities may influence the risk associated with paid work, and the integration of work in the community for adulthood. Samples are primarily rural except for Peru, but work and education trade-offs may be larger in rural areas because of types of work and distance to schools. Appendix I report estimates by urban-rural locality and their corresponding Romano-Wolf p-values. The estimates show little variation across the four countries except for some estimates. In India, the detrimental associations of domestic or economic work are primarily seen in rural areas for self-efficacy, not for self-esteem, while in Vietnam, the negative associations from domestic work instead of school are seen in urban areas.

Table 2.6: Estimates for generalised self-efficacy by sex

	Ethiopia		India		Peru		Vietnam	
	Male	Female	Male	Female	Male	Female	Male	Female
Leisure omitted								
Domestic work, age 15	-0.036*	-0.021	-0.008	-0.026	0.014	-0.003	-0.008	-0.019
	(0.020)	(0.024)	(0.022)	(0.021)	(0.014)	(0.013)	(0.019)	(0.013)
Economic work, age 15	-0.013	-0.034	-0.001	-0.012	0.012	0.005	-0.004	-0.007
	(0.014)	(0.022)	(0.014)	(0.012)	(0.011)	(0.021)	(0.014)	(0.014)
Studying outside school	0.006	0.001	0.030	-0.001	0.008	0.040*	0.013	0.005
	(0.031)	(0.029)	(0.025)	(0.015)	(0.018)	(0.020)	(0.012)	(0.011)
Attending school, age 15	-0.001	0.003	0.021*	0.014	0.029	0.035*	-0.006	0.013
	(0.018)	(0.023)	(0.012)	(0.012)	(0.010)	(0.017)	(0.014)	(0.010)
Sleep, age 15	0.040	-0.010	-0.005	-0.030	-0.007	0.006	0.022	-0.040**
	(0.020)	(0.039)	(0.034)	(0.035)	(0.019)	(0.021)	(0.017)	(0.016)
Self-efficacy, age 12	0.050	0.143***	0.148***	0.091**	0.166***	0.250***	0.156***	0.189***
	(0.042)	(0.044)	(0.034)	(0.039)	(0.048)	(0.034)	(0.051)	(0.038)
Constant	-0.326	-0.405	0.037	0.836*	-0.396	-1.584***	-0.682*	0.383
	(0.410)	(0.578)	(0.460)	(0.427)	(0.356)	(0.349)	(0.352)	(0.400)
R-squared	0.187	0.220	0.187	0.148	0.127	0.182	0.122	0.175
domestic=economic work	0.212	0.562	0.701	0.513	0.872	0.759	0.767	0.348
study=leisure	0.878	0.948	0.682	0.454	0.339	0.854	0.370	0.611
domestic work=leisure	0.133	0.312	0.247	0.056	0.253	0.018	0.896	0.017
economic work=leisure	0.428	0.093	0.074	0.002	0.183	0.271	0.790	0.056
School omitted								
Domestic work, age 15	-0.036	-0.024	-0.029	-0.039**	-0.001	-0.027*	-0.002	-0.031*
	(0.023)	(0.023)	(0.024)	(0.019)	(0.012)	(0.011)	(0.016)	(0.012)
Economic work, age 15	-0.012	-0.037	-0.022*	-0.025**	-0.013	-0.020	0.002	-0.020*
	(0.015)	(0.021)	(0.012)	(0.007)	(0.011)	(0.024)	(0.007)	(0.010)
Studying outside school	0.006	-0.002	0.009	-0.015	-0.010	0.012	0.019	-0.007
	(0.040)	(0.028)	(0.022)	(0.019)	(0.018)	(0.026)	(0.019)	(0.015)
Leisure, age 15	0.001	-0.003	-0.021*	-0.014	-0.023	-0.040**	0.006	-0.013
	(0.018)	(0.023)	(0.012)	(0.012)	(0.012)	(0.016)	(0.014)	(0.009)
Sleep, age 15	0.041	-0.013	-0.027	-0.044	-0.028	-0.023	0.028	-0.052**
	(0.021)	(0.033)	(0.036)	(0.035)	(0.019)	(0.023)	(0.017)	(0.019)
Self-efficacy, age 12	0.050	0.143***	0.148***	0.091**	0.171***	0.256***	0.157***	0.189***
	(0.042)	(0.044)	(0.034)	(0.039)	(0.049)	(0.033)	(0.051)	(0.038)
Constant	0.032	-0.671	0.475	0.306	0.168	-0.637	-0.433	0.888
	(0.452)	(0.466)	(0.411)	(0.385)	(0.342)	(0.402)	(0.505)	(0.561)
R-squared	0.187	0.220	0.187	0.148	0.124	0.178	0.123	0.175
domestic=economic work	0.212	0.562	0.701	0.513	0.529	0.818	0.773	0.390
study=leisure	0.860	0.968	0.238	0.934	0.544	0.017	0.259	0.571
domestic work=leisure	0.085	0.385	0.727	0.243	0.238	0.467	0.676	0.169
economic work=leisure	0.349	0.137	0.967	0.330	0.477	0.405	0.776	0.647
Observations	815	736	958	798	859	839	874	821

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. All estimates control for child, caregiver and household characteristics, lagged time allocation, as well as lagged mathematics and self-efficacy scores. Standard errors are reported in parentheses, clustered at each country's cluster level. Test for equality of coefficients report the p-values.

Table 2.7: Estimates for generalised self-esteem by sex

	Ethiopia		India		Peru		Vietnam	
	Male	Female	Male	Female	Male	Female	Male	Female
Leisure omitted								
Domestic work, age 15	-0.020	-0.012	0.026	-0.019	0.011	0.008	-0.001	0.001
	(0.015)	(0.022)	(0.027)	(0.021)	(0.018)	(0.012)	(0.016)	(0.014)
Economic work, age 15	0.016	-0.014	0.014	-0.019	0.012	0.009	0.001	0.013
	(0.013)	(0.019)	(0.016)	(0.014)	(0.019)	(0.020)	(0.010)	(0.012)
Studying outside school	0.011	0.010	0.029	-0.025	0.032	0.067**	0.030*	0.027
	(0.030)	(0.030)	(0.025)	(0.024)	(0.024)	(0.022)	(0.015)	(0.021)
Attending school, age 15	0.037**	-0.005	0.017	-0.015	0.019	0.040**	0.002	0.022
	(0.017)	(0.023)	(0.015)	(0.012)	(0.013)	(0.012)	(0.011)	(0.014)
Sleep, age 15	0.029	0.007	-0.041	-0.048	-0.012	0.030	0.010	-0.028
	(0.024)	(0.046)	(0.025)	(0.036)	(0.021)	(0.022)	(0.017)	(0.027)
Self-esteem, age 12	0.129***	-0.001	0.060*	0.051	0.153***	0.222***	0.197***	0.189***
	(0.036)	(0.029)	(0.030)	(0.031)	(0.039)	(0.030)	(0.043)	(0.034)
Constant	-0.648	-0.142	-0.116	0.526	-1.090***	-1.081**	-1.399***	-0.357
	(0.450)	(0.535)	(0.443)	(0.488)	(0.346)	(0.469)	(0.317)	(0.497)
R-squared	0.206	0.234	0.109	0.112	0.117	0.134	0.149	0.129
domestic=economic work	0.003	0.895	0.664	0.972	0.995	0.945	0.917	0.465
study=leisure	0.527	0.625	0.534	0.685	0.588	0.244	0.166	0.807
domestic work=leisure	0.009	0.756	0.724	0.844	0.535	0.039	0.874	0.242
economic work=leisure	0.234	0.618	0.678	0.661	0.574	0.160	0.922	0.472
School omitted								
Domestic work, age 15	-0.058**	-0.007	0.009	-0.004	0.000	-0.018	-0.001	-0.023
	(0.020)	(0.023)	(0.024)	(0.020)	(0.015)	(0.012)	(0.015)	(0.016)
Economic work, age 15	-0.021	-0.009	-0.003	-0.004	-0.006	-0.018	0.000	-0.011
	(0.017)	(0.018)	(0.007)	(0.010)	(0.013)	(0.019)	(0.008)	(0.012)
Studying outside school	-0.026	0.015	0.012	-0.010	0.018	0.038	0.032	0.000
	(0.040)	(0.030)	(0.019)	(0.024)	(0.021)	(0.023)	(0.019)	(0.019)
Leisure, age 15	-0.037**	0.005	-0.017	0.015	-0.017	-0.041**	0.001	-0.030*
	(0.017)	(0.023)	(0.015)	(0.012)	(0.013)	(0.013)	(0.011)	(0.015)
Sleep, age 15	-0.008	0.012	-0.058	-0.033	-0.027	0.003	0.010	-0.052**
	(0.025)	(0.034)	(0.027)	(0.038)	(0.020)	(0.022)	(0.016)	(0.026)
Self-esteem, age 12	0.129***	-0.000	0.060*	0.051	0.154***	0.223***	0.198***	0.189***
	(0.036)	(0.029)	(0.030)	(0.031)	(0.038)	(0.030)	(0.043)	(0.033)
Constant	0.017	0.035	0.719	0.289	-0.662**	-0.527	-1.320**	0.376
	(0.549)	(0.491)	(0.450)	(0.448)	(0.292)	(0.402)	(0.478)	(0.560)
R-squared	0.206	0.234	0.109	0.112	0.116	0.134	0.149	0.132
domestic=economic work	0.003	0.895	0.664	0.972	0.755	0.992	0.936	0.429
study=leisure	0.713	0.736	0.254	0.310	0.194	0.002	0.048	0.178
domestic work=leisure	0.184	0.606	0.355	0.375	0.397	0.151	0.887	0.693
economic work=leisure	0.228	0.471	0.395	0.178	0.554	0.253	0.908	0.178
Observations	815	736	958	798	859	839	874	821

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Refer to table notes in Table 2.6 above.

2.8 Discussion and conclusions

My findings show that in Ethiopia, India and Vietnam, domestic work is the most harmful form of work for adolescents' self-efficacy especially if it reduces time for school, indicating there is an immediate cost to work, especially when it comes at the price of education (which is a long-term measure of risk mitigation). While the findings show that there are no competencies learned via work, as opposed to the previous qualitative literature about adolescents' work in the YL countries (Morrow and Boyden 2018; Boyden, Porter, and Zharkevich 2021), there are little detrimental associations for work at the cost of leisure, which could be explained by an environment where work is commonplace among adolescents, especially in an environment where adolescents are expected to contribute to the family.

There are few associations between economic work and self-esteem or self-efficacy, which in contrast to the initial hypotheses, was expected for Ethiopian adolescents being 'work-oriented' but is also seen in 'education-oriented' countries. However, there is some suggestive evidence that doing work in opposing 'gender roles' e.g., boys doing domestic work is associated with poorer self-esteem, demonstrating the importance of potential 'stigma' in the types of work adolescents do, based on their environment.

Estimates are mostly relevant for self-efficacy, suggesting that the influences of activities are different for self-efficacy and self-esteem. Since doing work and attending school are more task achievement-based time inputs, these activities may be more strongly associated to self-efficacy compared to self-esteem which are more affective. There may also be few significant associations with self-esteem because the social standings of work and attending school are considered of equal value in these communities.

Domestic work harms girls' self-efficacy more than boys, in contrast to Borga (2019) who does not find gendered differences. This difference to Borga (2019) is likely because I use the YL younger cohort, where adolescents do less paid work, but hides the prevalence of domestic work which burdens girls more, which means that if unpaid domestic work is not considered a form of work, these gendered inequalities are not captured. Regardless of the initial hypothesis that only Ethiopia and India are likely to have gendered gaps, all countries exhibit a female-bias.

In combination with findings by Keane, Krutikova, and Neal (2020), I show that domestic and economic work in the YL countries are detrimental for both adolescents' cognitive skills as well as their self-esteem and self-efficacy, but only if it crowds out school/study time rather than leisure. This expands on Borga (2019) who previously found that work activities (paid or unpaid) are associated with a reduction in cognitive and social and emotional competencies, which do not uncover how the results differ according to whether an additional hour of work come at the expense of fewer hours in school compared to fewer hours in leisure. In addition to both these studies, I find that attending school or studying at the expense of leisure are only productive for adolescents' self-efficacy and self-esteem in Peru, not in the other three YL countries, which may be explained by Peru's sample (i.e., nationally representative and urban), as well as the possibility that Peruvian adolescents are better supervised or work in safer environments compared to other YL adolescents. While not statistically significant, the coefficient estimates of additional time studying outside school instead of attending school or leisure is still positive for both Peru and Vietnam, which suggests better education systems compared to Ethiopia and India, that may be positively related to adolescent competencies. Conversely, the education systems in Ethiopia and India may on average, not allow beneficial environments (good peers, teachers), that allow socio-emotional development.

In conclusion, work in developing countries may be harmful to youths' competencies, but it depends on the country studied, the type of work, and the activities within the time budget. This relates back to Rogoff (2003) about how adolescents' competencies developed from work and play depend on the cultural environments. This is highlighted through the cross-country differences; differences in gender norms may be driving the vulnerabilities of work for girls, and the differential benefits of educational activities on competencies. This provides important context in analyzing child labor, which is of a sensitive nature in policy and the media. Policies that aim to reduce adolescents' time in work should consider whether spare time will be shifted into education (if returns are high enough) and not leisure, given barriers to education.

Future studies that examine young people's time allocation in developing countries should account for the full set of activities. Additionally, this study is limited since YL data is unable to distinguish between different types of "leisure" activities i.e., resting and playing. Note also that the YL data are not nationally representative and have poor-biased sampling, and thus these findings cannot be generalised. Rather, this research exemplifies how adolescents' time use are related to their competencies in particularly low-resource settings. Future research in developing countries should collect more disaggregated information on leisure to help broaden empirical research on young people's development in a more holistic way rather than the sole focus on child labor.

2.9 Appendix A

2.9.1 Indicators for self-esteem and self-efficacy

Table A2.1: List of questions for self-esteem and self-efficacy measures in the YL data

Generalised self-efficacy scale
1. I can always manage to solve difficult problems if I try hard enough
2. If someone opposes me, I can find the means and ways to get what I want
3. It is easy for me to stick to my aims and accomplish my goals
4. I am confident that I could deal efficiently with unexpected events
5. Thanks to my resourcefulness, I know how to handle unforeseen situations
6. I can solve most problems if I invest the necessary effort
7. I can remain calm when facing difficulties because I can rely on my coping abilities
8. When I am confronted with a problem, I can usually find several solutions
9. If I am in trouble, I can usually think of a solution
10. I can usually handle whatever comes my way
Generalised self-esteem scale
1. I do lots of important things
2. In general, I like being the way I am
3. Overall, I have a lot to be proud of
4. I can do things as well as most people
5. Other people think I am a good person
6. A lot of things about me are good
7. I'm as good as most other people
8. When I do something, I do it well

Each score; generalised self-esteem and generalised self-efficacy, are made up of the 8 and 10 items listed respectively. All items are positively worded and measured in the same direction because piloting of reverse-coded items did not perform well for the self-esteem scale, and found to be corrected when positively worded. More details on the validity of the scores are reported in Yorke and Portela (2018).

2.9.2 Validity of the self-esteem and self-efficacy scores

Table A2.2: Cronbach alpha's for self-esteem and self-efficacy in Ethiopia

Item	Obs	Sign	item-test correlation	item-rest correlation	average inter item correlation	alpha
Self-efficacy items						
I can always manage to solve difficult problems if I try hard enough	1550	+	0.546	0.405	0.257	0.757
If someone opposes me, I can find the means and ways to get what I want	1548	+	0.457	0.302	0.271	0.770
It is easy for me to stick to my aims and accomplish my goals	1545	+	0.570	0.433	0.253	0.753
I am confident that I could deal efficiently with unexpected events	1546	+	0.642	0.521	0.242	0.742
Thanks to my resourcefulness, I know how to handle unforeseen circumstances	1549	+	0.600	0.469	0.248	0.748
I can solve most problems if I invest the necessary effort	1550	+	0.482	0.331	0.267	0.766
I can remain calm when facing difficulties because I can rely on my coping abilities	1546	+	0.594	0.461	0.250	0.750
When I am confronted with a problem, I can usually find several solutions	1547	+	0.631	0.507	0.244	0.743
If I am in trouble, I can usually think of a solution	1550	+	0.571	0.435	0.253	0.753
I can usually handle whatever comes in my way	1551	+	0.633	0.509	0.243	0.743
Test scale					0.253	0.771
Self-esteem items						
I do lots of important things	1550	+	0.610	0.447	0.244	0.693
In general, I like being the way I am	1551	+	0.586	0.417	0.249	0.699
Overall, I have a lot to be proud of	1550	+	0.547	0.370	0.258	0.709
I can do things as well as most people	1551	+	0.563	0.390	0.254	0.705
Other people think I am a good person	1540	+	0.561	0.387	0.255	0.705
A lot of things about me are good	1551	+	0.662	0.512	0.232	0.679
I'm as good as most other people	1546	+	0.577	0.406	0.251	0.701
When I do something, I do it well	1551	+	0.582	0.412	0.250	0.700
Test scale					0.249	0.726

Table A2.3: Cronbach alpha's for self-esteem and self-efficacy in India

Item	Obs	Sign	item-test correlation	item-rest correlation	average inter item correlation	alpha
Self-efficacy items						
I can always manage to solve difficult problems if I try hard enough	1754	+	0.466	0.305	0.233	0.733
If someone opposes me, I can find the means and ways to get what I want	1746	+	0.452	0.289	0.235	0.734
It is easy for me to stick to my aims and accomplish my goals	1726	+	0.411	0.240	0.241	0.741
I am confident that I could deal efficiently with unexpected events	1747	+	0.610	0.473	0.211	0.706
Thanks to my resourcefulness, I know how to handle unforeseen circumstances	1738	+	0.638	0.507	0.207	0.702
I can solve most problems if I invest the necessary effort	1741	+	0.520	0.365	0.225	0.723
I can remain calm when facing difficulties because I can rely on my coping abilities	1750	+	0.602	0.462	0.213	0.708
When I am confronted with a problem, I can usually find several solutions	1741	+	0.603	0.466	0.212	0.708
If I am in trouble, I can usually think of a solution	1749	+	0.591	0.451	0.214	0.710
I can usually handle whatever comes in my way	1750	+	0.591	0.452	0.214	0.710
Test scale					0.220	0.739
Self-esteem						
I do lots of important things	1740	+	0.543	0.346	0.187	0.617
In general, I like being the way I am	1750	+	0.458	0.243	0.204	0.642
Overall, I have a lot to be proud of	1732	+	0.498	0.291	0.196	0.631
I can do things as well as most people	1755	+	0.483	0.272	0.200	0.636
Other people think I am a good person	1710	+	0.602	0.418	0.174	0.596
A lot of things about me are good	1738	+	0.630	0.454	0.169	0.587
I'm as good as most other people	1744	+	0.594	0.407	0.176	0.599
When I do something, I do it well	1752	+	0.502	0.296	0.195	0.629
Test scale					0.188	0.649

Table A2.4: Cronbach alpha's for self-esteem and self-efficacy in Peru

Item	Obs	Sign	item-test correlation	item-rest correlation	average inter item correlation	alpha
Self-efficacy items						
I can always manage to solve difficult problems if I try hard enough	1698	+	0.646	0.524	0.236	0.736
If someone opposes me, I can find the means and ways to get what I want	1698	+	0.340	0.173	0.285	0.782
It is easy for me to stick to my aims and accomplish my goals	1698	+	0.531	0.387	0.255	0.754
I am confident that I could deal efficiently with unexpected events	1696	+	0.529	0.384	0.255	0.755
Thanks to my resourcefulness, I know how to handle unforeseen circumstances	1698	+	0.611	0.482	0.242	0.742
I can solve most problems if I invest the necessary effort	1696	+	0.606	0.476	0.243	0.743
I can remain calm when facing difficulties because I can rely on my coping abilities	1697	+	0.639	0.516	0.237	0.737
When I am confronted with a problem, I can usually find several solutions	1698	+	0.577	0.441	0.247	0.747
If I am in trouble, I can usually think of a solution	1698	+	0.598	0.466	0.244	0.744
I can usually handle whatever comes in my way	1697	+	0.612	0.483	0.242	0.741
Test scale					0.249	0.768
Self-esteem						
I do lots of important things	1698	+	0.559	0.387	0.266	0.717
In general, I like being the way I am	1698	+	0.608	0.446	0.255	0.705
Overall, I have a lot to be proud of	1698	+	0.591	0.426	0.258	0.709
I can do things as well as most people	1698	+	0.607	0.447	0.255	0.705
Other people think I am a good person	1697	+	0.571	0.402	0.263	0.714
A lot of things about me are good	1697	+	0.637	0.483	0.248	0.698
I'm as good as most other people	1698	+	0.572	0.403	0.263	0.714
When I do something, I do it well	1697	+	0.594	0.429	0.258	0.708
Test scale					0.258	0.736

Table A2.5: Cronbach alpha's for self-esteem and self-efficacy in Vietnam

Item	Obs	Sign	item-test correlation	item-rest correlation	average inter item correlation	alpha
Self-efficacy						
I can always manage to solve difficult problems if I try hard enough	1695	+	0.462	0.291	0.201	0.694
If someone opposes me, I can find the means and ways to get what I want	1687	+	0.324	0.137	0.221	0.718
It is easy for me to stick to my aims and accomplish my goals	1685	+	0.546	0.389	0.189	0.677
I am confident that I could deal efficiently with unexpected events	1686	+	0.616	0.475	0.178	0.661
Thanks to my resourcefulness, I know how to handle unforeseen circumstances	1680	+	0.552	0.397	0.188	0.675
I can solve most problems if I invest the necessary effort	1693	+	0.478	0.309	0.198	0.690
I can remain calm when facing difficulties because I can rely on my coping abilities	1689	+	0.616	0.475	0.178	0.662
When I am confronted with a problem, I can usually find several solutions	1693	+	0.578	0.427	0.184	0.670
If I am in trouble, I can usually think of a solution	1692	+	0.489	0.322	0.197	0.688
I can usually handle whatever comes in my way	1690	+	0.564	0.411	0.186	0.673
Test scale					0.192	0.704
Self-esteem						
I do lots of important things	1681	+	0.549	0.353	0.187	0.617
In general, I like being the way I am	1690	+	0.436	0.218	0.211	0.652
Overall, I have a lot to be proud of	1689	+	0.527	0.327	0.192	0.625
I can do things as well as most people	1689	+	0.572	0.381	0.183	0.610
Other people think I am a good person	1666	+	0.500	0.296	0.197	0.632
A lot of things about me are good	1680	+	0.597	0.413	0.178	0.602
I'm as good as most other people	1679	+	0.601	0.418	0.177	0.600
When I do something, I do it well	1687	+	0.534	0.333	0.190	0.622
Test scale					0.189	0.651

Table A2.6: Description of standardised socio-emotional scores, age 12 and 15

	Raw score				Standardised score			
	Self-esteem		Self-efficacy		Self-esteem		Self-efficacy	
	Age 12	Age 15	Age 12	Age 15	Age 12	Age 15	Age 12	Age 15
Ethiopia								
Mean	25.12	25.00	29.26	30.34	0.01	0.00	0.01	0.01
Median	25.00	25.00	30.00	30.00	-0.06	-0.04	0.11	-0.07
SD	3.09	2.49	4.01	3.26	0.63	0.59	0.60	0.57
Min	6.00	14.00	5.00	17.00	-3.22	-2.10	-2.78	-2.24
Max	32.00	32.00	40.00	40.00	1.43	1.68	1.63	1.70
India								
Mean	0.01	0.00	0.01	0.00	24.58	24.47	29.31	31.15
Median	-0.16	-0.14	-0.03	-0.06	24.00	24.00	30.00	31.00
SD	0.60	0.54	0.62	0.55	2.90	2.54	4.74	3.33
Min	-2.66	-1.89	-3.00	-2.78	11.00	12.00	5.00	8.00
Max	1.59	1.75	1.61	1.65	32.00	32.00	40.00	40.00
Peru								
Mean	0.01	0.00	0.01	0.00	24.96	25.08	29.55	30.42
Median	-0.02	-0.05	0.04	-0.07	25.00	25.00	30.00	30.00
SD	0.57	0.59	0.51	0.57	2.70	2.42	3.63	3.17
Min	-2.08	-3.73	-1.82	-2.24	14.00	10.00	6.00	18.00
Max	1.53	1.71	1.59	1.70	32.00	32.00	40.00	40.00
Vietnam								
Mean	0.01	0.01	0.01	0.01	22.20	22.08	28.34	28.74
Median	-0.01	0.03	0.01	0.03	22.00	22.00	28.00	29.00
SD	0.56	0.54	0.51	0.52	2.53	2.41	2.95	2.82
Min	-3.14	-2.54	-2.54	-1.87	8.00	6.00	14.00	17.00
Max	2.16	1.98	1.88	2.16	32.00	30.00	39.00	40.00

Table A2.7: Sample description of adolescents not included in the analytical sample

	Ethiopia	India	Peru	Vietnam
Female	0.44	0.56	0.52	0.52
Age in months	181.07	179.89	179.49	183.17
Height for age z-score, age 5	-1.59	-1.95	-2.03	-1.48
Mathematics IRT score, age 12	431.19	441.89	474.79	567.12
Oromo/ Scheduled Caste	0.32	0.19		0.00
Amhara/Backward Caste/Majority Kinh	0.25	0.47		0.78
Tigrian/ Scheduled Tribe	0.18	0.14		0.00
Other ethnicity/Caste	0.25	0.20		0.22
Mother's language: Spanish			0.50	
No religion	0.00	0.00	0.02	0.85
Christian	0.00	0.06	0.00	0.02
Muslim	0.17	0.04	0.00	0.00
Buddhist	0.00	0.01	0.00	0.08
Hindu	0.00	0.90	0.00	0.00
Catholic	0.01	0.00	0.85	0.00
Protestant	0.06	0.00	0.00	0.02
Orthodox	0.74	0.00	0.00	0.00
Evangelist	0.00	0.00	0.12	0.00
Mormon	0.00	0.00	0.01	0.00
Ancestor Worship	0.00	0.00	0.00	0.02
Cao Dai	0.00	0.00	0.00	0.02
Other	0.01	0.00	0.00	0.00
Mother's age, child 0/1	27.37	24.12	29.05	26.55
Caregiver's agency score, adolescent age 8	-0.04	-0.26	-0.02	0.00
Caregiver's pride score, adolescent age 8	-0.06	-0.22	-0.07	-0.10
Caregiver's education:				
$\leq$ Incomplete primary education	0.86	0.87	0.53	0.46
Up to lower secondary	0.10	0.10	0.21	0.45
Up to upper secondary	0.00	0.00	0.13	0.02
Higher education	0.04	0.02	0.13	0.07
Adolescent is oldest in household	0.30	0.37	0.34	0.44
Number of siblings	3.67	1.63	2.50	1.70
Both parents in household	0.73	0.88	0.73	0.92
Household size	5.55	4.75	4.96	4.36
Household in urban location	0.39	0.17	0.63	0.31
Wealth tercile	0.40	0.58	0.55	0.67
Max observations	252	135	109	196

2.10 Appendix B

2.10.1 Time allocation across age

Table A2.8: Time allocation across age for Ethiopia and India

	Age 5		Age 8		Age 12		Age 15	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ethiopia (unconditional hours)								
Domestic work	1.13	1.83	2.47	1.96	2.46	1.70	2.72	1.78
Economic work	0.57	1.53	1.53	2.25	1.65	2.15	1.84	2.53
Attending school	1.92	3.18	4.90	2.54	5.62	1.76	5.33	1.97
Studying outside school	0.26	0.55	0.99	0.88	1.50	0.94	1.84	1.16
Leisure	9.00	3.50	4.44	2.39	3.43	1.73	3.42	1.78
Sleep	10.66	1.24	9.67	1.00	9.34	1.00	8.85	0.99
Ethiopia (conditional hours i.e., only those performing activity)								
Domestic work	2.91	1.87	2.92	1.79	2.83	1.51	3.00	1.63
Economic work	3.33	2.12	3.65	2.08	3.38	1.90	3.76	2.42
Attending school	6.89	1.42	5.90	1.35	5.93	1.19	5.83	1.15
Studying outside school	1.24	0.50	1.48	0.67	1.71	0.80	2.09	1.00
Leisure	9.01	3.48	4.45	2.39	3.45	1.72	3.47	1.75
Sleep	10.66	1.24	9.67	1.00	9.34	1.00	8.85	0.99
India (unconditional hours)								
Domestic work	0.23	0.64	0.55	0.86	1.00	0.99	1.36	1.27
Economic work	0.00	0.03	0.02	0.35	0.21	1.19	0.82	2.47
Attending school	5.74	2.07	7.68	1.12	8.00	1.75	7.83	3.01
Studying outside school	1.04	1.14	1.83	1.10	1.92	1.16	2.11	1.40
Leisure	5.72	2.82	4.77	1.68	3.92	1.63	3.57	1.79
Sleep	9.83	0.93	9.14	0.92	8.96	0.85	8.29	0.87
India (conditional hours i.e., only those performing activity)								
Domestic work	1.42	0.90	1.49	0.78	1.42	0.89	1.79	1.17
Economic work	1.00	0.00	2.32	2.65	4.38	3.37	5.90	3.73
Attending school	6.24	1.25	7.76	0.81	8.27	0.95	8.85	1.09
Studying outside school	1.68	1.01	2.01	0.98	2.05	1.08	2.46	1.19
Leisure	5.73	2.81	4.77	1.68	3.93	1.63	3.59	1.78
Sleep	9.83	0.93	9.14	0.92	8.96	0.85	8.29	0.87

Table A2.9: Time allocation across age for Peru and Vietnam

	Age 5		Age 8		Age 12		Age 15	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Peru (unconditional hours)								
Domestic work	0.78	1.11	1.35	1.21	2.03	1.38	1.99	1.54
Economic work	0.09	0.58	0.26	0.68	0.59	1.10	0.53	1.53
Attending school	3.64	1.84	5.98	0.98	6.06	0.85	6.87	2.00
Studying outside school	1.20	0.84	1.87	0.83	1.85	0.91	2.07	1.09
Leisure	4.09	2.13	4.16	1.70	3.66	1.44	3.49	1.59
Sleep	10.11	1.16	9.64	0.97	9.53	0.99	8.67	1.17
Peru (conditional hours i.e., only those performing activity)								
Domestic work	1.62	1.09	1.80	1.07	2.26	1.27	2.28	1.43
Economic work	2.01	1.87	1.58	0.88	2.09	1.09	2.90	2.42
Attending school	4.41	0.83	6.05	0.76	6.08	0.78	7.23	1.27
Studying outside school	1.47	0.68	1.90	0.79	1.89	0.87	2.18	1.00
Leisure	4.10	2.13	4.18	1.68	3.67	1.43	3.50	1.58
Sleep	10.12	1.13	9.65	0.95	9.53	0.99	8.67	1.15
Vietnam (unconditional hours)								
Domestic work	0.11	0.49	0.80	0.98	1.56	1.33	1.72	1.42
Economic work	0.01	0.12	0.12	0.62	0.45	1.09	1.47	2.80
Attending school	5.48	2.73	4.97	1.37	5.39	1.54	5.01	2.84
Studying outside school	0.61	0.77	2.78	1.51	2.64	1.42	2.55	1.85
Leisure	7.74	2.71	5.62	1.73	4.92	2.09	4.71	2.49
Sleep	10.01	1.03	9.70	0.99	9.02	1.03	8.47	1.16
Vietnam (conditional hours i.e., only those performing activity)								
Domestic work	1.72	1.03	1.53	0.84	1.91	1.22	2.00	1.34
Economic work	1.80	1.30	2.55	1.45	2.00	1.51	3.92	3.37
Attending school	5.88	2.38	5.03	1.26	5.57	1.20	6.26	1.51
Studying outside school	1.34	0.57	2.86	1.45	2.82	1.28	3.29	1.41
Leisure	7.75	2.70	5.62	1.72	4.94	2.07	4.71	2.49

2.11 Appendix C

2.11.1 Full regression estimates

Table A2.10: Full estimates, attending school omitted

	Ethiopia		India		Peru		Vietnam	
	SEF	SES	SEF	SES	SEF	SES	SEF	SES
Domestic work, age 15	-0.031**	-0.037**	-0.037**	0.007	-0.013	-0.007	-0.015	-0.008
	(0.014)	(0.018)	(0.015)	(0.015)	(0.008)	(0.009)	(0.008)	(0.011)
Economic work, age 15	-0.017	-0.012	-0.025**	-0.006	-0.012	-0.011	-0.007	-0.003
	(0.012)	(0.015)	(0.009)	(0.005)	(0.011)	(0.011)	(0.007)	(0.007)
Studying outside school	-0.002	-0.005	-0.006	0.001	-0.002	0.024*	0.011	0.019
	(0.031)	(0.033)	(0.013)	(0.014)	(0.015)	(0.014)	(0.012)	(0.015)
Leisure, age 15	-0.002	-0.020	-0.013	0.004	-0.027**	-0.029**	-0.001	-0.009
	(0.016)	(0.016)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Sleep, age 15	0.013	-0.000	-0.036	-0.048	-0.023	-0.014	-0.005	-0.012
	(0.013)	(0.020)	(0.033)	(0.025)	(0.013)	(0.015)	(0.014)	(0.016)
Lagged score, age 12	0.081**	0.073***	0.115***	0.057**	0.208***	0.199***	0.170***	0.187***
	(0.029)	(0.020)	(0.025)	(0.023)	(0.028)	(0.018)	(0.032)	(0.031)
Adolescent characteristics								
Female	0.002	0.032	-0.031	0.016	-0.018	0.056*	0.013	-0.003
	(0.047)	(0.051)	(0.041)	(0.043)	(0.024)	(0.028)	(0.027)	(0.034)
Age in months	-0.000	-0.002	0.008**	-0.001	-0.000	0.003	0.006	0.002
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
Height-for-age z-score, age 5	0.020*	0.021	0.001	0.005	0.012	0.019	0.023	0.022**
	(0.011)	(0.013)	(0.012)	(0.014)	(0.011)	(0.014)	(0.014)	(0.009)
Maths IRT score, age 12	0.000	-0.000	0.001***	0.000	0.001***	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ethnicity or Caste (ref category: Omoro (ET), Backward Caste (IN) and Majority Kinh (VN))								
Mother's first language is Spanish					0.012	-0.044		
					(0.053)	(0.032)		
Scheduled Caste (IN)/ Amhara (ET)	-0.142	-0.071	0.026	0.027				
	(0.087)	(0.085)	(0.038)	(0.036)				
Scheduled Tribe (IN)/Tigrian (ET)	-0.146**	-0.184**	0.021	0.026				
	(0.063)	(0.085)	(0.066)	(0.042)				
Other ethnicity/caste	-0.191***	-0.126**	-0.034	-0.005			-0.128*	-0.089**
	(0.052)	(0.055)	(0.047)	(0.030)			(0.066)	(0.042)
Family and household characteristics								
Mother's age when child was 0/1	-0.000	0.001	-0.001	-0.001	0.001	0.003	-0.003	-0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Caregiver's educ: Up to lower secondary	0.030	0.104*	-0.004	-0.072*	-0.036	0.015	-0.023	0.009
	(0.062)	(0.055)	(0.047)	(0.036)	(0.033)	(0.037)	(0.043)	(0.054)
Caregiver's educ: Up to upper secondary	-0.173	-0.039	-0.539**	-0.476***	-0.058	-0.028	0.016	0.019
	(0.419)	(0.305)	(0.201)	(0.097)	(0.055)	(0.052)	(0.105)	(0.095)
Caregiver's educ: Higher education	0.073	0.050	0.146**	-0.036	-0.011	0.025	-0.044	0.000
	(0.074)	(0.056)	(0.052)	(0.057)	(0.046)	(0.047)	(0.056)	(0.090)
Caregiver's agency index, child age 8	0.001	0.051**	-0.032	0.027	0.039	0.015	-0.003	-0.020
	(0.019)	(0.023)	(0.021)	(0.028)	(0.024)	(0.032)	(0.024)	(0.037)
Caregiver's pride index, child age 8	0.009	-0.005	0.030	-0.040*	0.013	0.027	0.026	0.051**
	(0.032)	(0.032)	(0.021)	(0.023)	(0.020)	(0.019)	(0.016)	(0.023)

Continued in the next page

Table A2.10 cont'd: Full estimates, attending school omitted

Continued from the previous page								
	Ethiopia		India		Peru		Vietnam	
	SEF	SES	SEF	SES	SEF	SES	SEF	SES
Adolescent is oldest in household	0.054	-0.018	0.011	0.007	0.053	0.074	0.003	0.019
	(0.037)	(0.030)	(0.032)	(0.025)	(0.042)	(0.058)	(0.034)	(0.035)
Number of siblings	-0.000	-0.016**	0.013	0.002	-0.005	-0.002	0.021	0.022*
	(0.012)	(0.007)	(0.012)	(0.015)	(0.013)	(0.014)	(0.013)	(0.012)
Both parents in household	-0.001	-0.027	0.019	0.011	0.036	0.074**	0.030	0.045
	(0.037)	(0.032)	(0.045)	(0.046)	(0.048)	(0.034)	(0.051)	(0.044)
Household size	0.022**	0.029**	0.002	-0.002	0.002	0.013	-0.020*	-0.021**
	(0.010)	(0.011)	(0.006)	(0.006)	(0.008)	(0.010)	(0.011)	(0.009)
Household in urban area	0.162***	0.054	-0.073	-0.046	0.012	-0.037	-0.311***	-0.212***
	(0.035)	(0.038)	(0.058)	(0.035)	(0.032)	(0.031)	(0.049)	(0.064)
Bottom wealth tercile	-0.094*	-0.113**	-0.035	-0.032	-0.028	-0.012	0.059	0.050
	(0.052)	(0.051)	(0.038)	(0.043)	(0.034)	(0.042)	(0.037)	(0.055)
Middle wealth tercile	-0.057	-0.065	-0.003	-0.013	-0.014	-0.023	-0.020	0.024
	(0.047)	(0.045)	(0.040)	(0.043)	(0.035)	(0.036)	(0.030)	(0.038)
Lagged time inputs								
Domestic work, age 12	-0.002	-0.005	0.020	0.002	0.004	0.004	-0.000	0.006
	(0.010)	(0.012)	(0.012)	(0.020)	(0.012)	(0.012)	(0.012)	(0.014)
Economic work, age 12	-0.013*	-0.010	0.036	-0.012	0.026**	0.016	-0.028**	-0.034**
	(0.007)	(0.012)	(0.021)	(0.016)	(0.012)	(0.011)	(0.011)	(0.014)
Studying outside school, age 12	-0.006	0.012	0.026**	-0.007	0.027	0.035	0.011	0.005
	(0.012)	(0.019)	(0.011)	(0.015)	(0.020)	(0.021)	(0.017)	(0.016)
Leisure, age 12	-0.006	0.006	0.016*	-0.019	0.023*	0.013	-0.013	-0.005
	(0.008)	(0.012)	(0.009)	(0.013)	(0.011)	(0.018)	(0.011)	(0.010)
Sleep, age12	-0.035**	-0.028*	0.006	-0.026	0.043***	0.030*	0.007	0.019
	(0.013)	(0.015)	(0.018)	(0.021)	(0.015)	(0.015)	(0.020)	(0.014)
Constant	-0.009	0.469	-1.469**	0.677	-0.986	-1.567*	-0.733	-0.837
	(0.791)	(0.586)	(0.658)	(0.765)	(0.721)	(0.857)	(0.815)	(0.846)
R-squared	0.182	0.190	0.135	0.074	0.148	0.113	0.130	0.122
p-value joint test	0.036	0.045	0.026	0.137	0.186	0.013	0.263	0.163
p-value domestic = economic work	0.313	0.030	0.422	0.434	0.936	0.810	0.255	0.577
p-value study = leisure	0.983	0.540	0.681	0.833	0.057	0.001	0.113	0.058
p-value domestic work = leisure	0.081	0.274	0.089	0.876	0.202	0.115	0.240	0.940
p-value economic work = leisure	0.227	0.453	0.254	0.332	0.158	0.193	0.534	0.533
Observations	1,551	1,551	1,756	1,756	1,698	1,698	1,695	1,695

Note: ***p<0.01, **p<0.05, *p<0.1. Standard errors are reported in parentheses, clustered at each country's cluster level in Round 5 (age 15). All estimates control for adolescent, caregiver and household characteristics, time allocation at age 12 and month of interview. For brevity, adolescent's detailed religion indicators were controlled for but are not reported here.

Table A2.11: Full estimates, leisure omitted

	Ethiopia		India		Peru		Vietnam	
	SEF	SES	SEF	SES	SEF	SES	SEF	SES
Domestic work, age 15	-0.030*	-0.017	-0.025*	0.003	0.004	0.009	-0.015	-0.000
	(0.016)	(0.015)	(0.014)	(0.018)	(0.009)	(0.011)	(0.011)	(0.012)
Economic work, age 15	-0.016	0.009	-0.012	-0.010	0.011	0.011	-0.007	0.005
	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.014)	(0.010)	(0.009)
Studying outside school	-0.001	0.015	0.007	-0.003	0.018	0.044**	0.012	0.028*
	(0.025)	(0.025)	(0.016)	(0.015)	(0.012)	(0.013)	(0.008)	(0.014)
School, age 15	0.002	0.020	0.013	-0.004	0.027**	0.027**	0.001	0.008
	(0.016)	(0.016)	(0.010)	(0.010)	(0.010)	(0.008)	(0.010)	(0.009)
Sleep, age 15	0.015	0.020	-0.023	-0.052*	-0.002	0.005	-0.004	-0.004
	(0.021)	(0.023)	(0.034)	(0.027)	(0.011)	(0.014)	(0.013)	(0.017)
Lagged score, age 12	0.081**	0.073***	0.115***	0.057**	0.206***	0.199***	0.170***	0.187***
	(0.029)	(0.020)	(0.025)	(0.023)	(0.028)	(0.018)	(0.032)	(0.031)
Adolescent characteristics								
Female	0.002	0.032	-0.031	0.016	-0.022	0.054*	0.014	-0.003
	(0.047)	(0.051)	(0.041)	(0.043)	(0.024)	(0.028)	(0.027)	(0.033)
Age in months	-0.000	-0.002	0.008**	-0.001	-0.001	0.003	0.006	0.002
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
Height-for-age z-score, age 5	0.020*	0.021	0.001	0.005	0.010	0.017	0.024	0.022**
	(0.011)	(0.013)	(0.012)	(0.014)	(0.010)	(0.013)	(0.014)	(0.009)
Maths IRT score, age 12	0.000	-0.000	0.001***	0.000	0.001***	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ethnicity or Caste (ref category: Omoro (ET), Backward Caste (IN) and Majority Kinh (VN))								
Mother's first language is Spanish					0.004	-0.050		
					(0.051)	(0.031)		
Scheduled Caste (IN)/Amhara (ET)	-0.142	-0.071	0.021	0.027				
	(0.087)	(0.085)	(0.066)	(0.036)				
Scheduled Tribe (IN)/Tigrian (ET)	-0.146**	-0.184**	0.026	0.026				
	(0.063)	(0.085)	(0.038)	(0.042)				
Other ethnicity/caste	-0.191***	-0.126**	-0.034	-0.005			-0.128*	-0.090**
	(0.052)	(0.055)	(0.047)	(0.030)			(0.066)	(0.041)
Family and household characteristics								
Mother's age when child was 0/1	-0.000	0.001	-0.001	-0.001	0.001	0.003	-0.003	-0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Caregiver's educ: Up to lower secondary	0.030	0.104*	-0.004	-0.072*	-0.033	0.016	-0.023	0.009
	(0.062)	(0.055)	(0.047)	(0.036)	(0.033)	(0.037)	(0.043)	(0.054)
Caregiver's educ: Up to upper secondary	-0.172	-0.039	-0.539**	-0.476***	-0.056	-0.027	0.014	0.017
	(0.419)	(0.305)	(0.201)	(0.097)	(0.053)	(0.051)	(0.105)	(0.096)
Caregiver's educ: Higher education	0.073	0.050	0.146**	-0.036	-0.015	0.024	-0.045	0.000
	(0.074)	(0.056)	(0.052)	(0.057)	(0.047)	(0.048)	(0.056)	(0.090)
Caregiver's agency index, child age 8	0.001	0.051**	-0.032	0.027	0.038	0.014	-0.003	-0.020
	(0.019)	(0.023)	(0.021)	(0.028)	(0.023)	(0.031)	(0.025)	(0.036)
Caregiver's pride index, child age 8	0.009	-0.005	0.030	-0.040*	0.013	0.026	0.026	0.051**
	(0.032)	(0.032)	(0.021)	(0.023)	(0.019)	(0.018)	(0.016)	(0.023)

Continued in the next page

Table A2.11 cont'd: Full estimates, leisure omitted

Continued from the previous page								
	Ethiopia		India		Peru		Vietnam	
	SEF	SES	SEF	SES	SEF	SES	SEF	SES
Oldest in household	0.054	-0.018	0.011	0.007	0.049	0.071	0.003	0.019
	(0.037)	(0.030)	(0.032)	(0.025)	(0.041)	(0.058)	(0.034)	(0.035)
Number of siblings	-0.000	-0.016**	0.013	0.002	-0.004	-0.001	0.021	0.022*
	(0.012)	(0.007)	(0.012)	(0.015)	(0.013)	(0.014)	(0.013)	(0.012)
Both parents in household	-0.001	-0.027	0.019	0.011	0.024	0.064*	0.030	0.045
	(0.037)	(0.032)	(0.045)	(0.046)	(0.050)	(0.033)	(0.051)	(0.044)
Household size	0.022**	0.029**	0.002	-0.002	0.001	0.012	-0.020*	-0.021**
	(0.010)	(0.011)	(0.006)	(0.006)	(0.007)	(0.010)	(0.011)	(0.009)
Household in urban area	0.162***	0.054	-0.073	-0.046	0.021	-0.034	-0.314***	-0.210***
	(0.035)	(0.038)	(0.058)	(0.035)	(0.036)	(0.032)	(0.048)	(0.064)
Bottom wealth tercile	-0.094*	-0.113**	-0.035	-0.032	-0.030	-0.015	0.060	0.050
	(0.052)	(0.051)	(0.038)	(0.043)	(0.035)	(0.041)	(0.037)	(0.055)
Middle wealth tercile	-0.057	-0.065	-0.003	-0.013	-0.015	-0.025	-0.019	0.024
	(0.047)	(0.045)	(0.040)	(0.043)	(0.036)	(0.036)	(0.029)	(0.038)
Lagged time inputs								
Domestic work, age 12	0.004	-0.011	0.003	0.021	-0.002	0.001	0.012	0.012
	(0.008)	(0.013)	(0.012)	(0.025)	(0.009)	(0.011)	(0.011)	(0.013)
Economic work, age 12	-0.007	-0.016	0.020	0.007	0.019*	0.012	-0.016	-0.029
	(0.008)	(0.011)	(0.025)	(0.019)	(0.011)	(0.009)	(0.013)	(0.018)
Studying outside school, age 12	0.000	0.005	0.010	0.012	0.019	0.029	0.023	0.010
	(0.015)	(0.014)	(0.013)	(0.015)	(0.018)	(0.020)	(0.015)	(0.014)
Leisure, age 12	0.006	-0.006	-0.016*	0.019	0.032	0.013	0.013	0.010
	(0.008)	(0.012)	(0.009)	(0.013)	(0.020)	(0.020)	(0.012)	(0.011)
Sleep, age12	-0.029*	-0.034**	-0.010	-0.007	0.038***	0.026*	0.019	0.025**
	(0.016)	(0.015)	(0.021)	(0.018)	(0.012)	(0.014)	(0.013)	(0.012)
Constant	-0.198	0.136	-1.385	0.308	-1.445*	-2.059**	-1.050	-1.198
	(0.760)	(0.525)	(0.818)	(0.747)	(0.727)	(0.812)	(0.800)	(0.700)
R-squared	0.182	0.190	0.135	0.074	0.149	0.113	0.130	0.122
p-value joint test	0.054	0.047	0.012	0.082	0.025	0.001	0.234	0.241
p-value domestic = economic work	0.313	0.030	0.422	0.434	0.598	0.915	0.236	0.555
p-value study = leisure	0.945	0.885	0.652	0.960	0.611	0.247	0.427	0.251
p-value domestic work = leisure	0.038	0.058	0.024	0.659	0.040	0.063	0.106	0.493
p-value economic work = leisure	0.169	0.447	0.011	0.259	0.236	0.178	0.355	0.683
Observations	1,551	1,551	1,756	1,756	1,698	1,698	1,695	1,695

Note: ***p<0.01, **p<0.05, *p<0.1. Standard errors are reported in parentheses, clustered at each country's cluster level in Round 5 (age 15). All estimates control for adolescent, caregiver and household characteristics, time allocation at age 12 and month of interview. For brevity, adolescent's detailed religion indicators were controlled for but are not reported here.

2.12 Appendix D

2.12.1 Multiple hypotheses tests

Table A2.12: Romano-wolf p-values of baseline VA estimates, school omitted

		Ethiopia			India			Peru			Vietnam	
School omitted	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.014	0.020	0.020	0.003	0.030	0.030	0.180	0.158	0.228	0.147	0.069	0.119
self-esteem	0.005	0.020	0.020	0.580	0.584	0.584	0.446	0.317	0.317	0.471	0.465	0.465
Economic work												
self-efficacy	0.090	0.129	0.267	0.000	0.010	0.010	0.258	0.376	0.545	0.277	0.337	0.525
self-esteem	0.260	0.386	0.386	0.383	0.297	0.297	0.246	0.327	0.545	0.612	0.654	0.654
Study												
self-efficacy	0.905	0.931	0.941	0.701	0.733	0.921	0.886	0.881	0.881	0.319	0.396	0.396
self-esteem	0.774	0.852	0.941	0.995	1.000	1.000	0.120	0.099	0.198	0.146	0.297	0.366
Leisure												
self-efficacy	0.883	0.960	0.960	0.134	0.188	0.287	0.009	0.010	0.010	0.961	0.980	0.980
self-esteem	0.074	0.149	0.238	0.667	0.693	0.693	0.006	0.010	0.010	0.220	0.287	0.475
Sleep												
self-efficacy	0.462	0.248	0.495	0.054	0.287	0.287	0.089	0.050	0.129	0.745	0.782	0.782
self-esteem	0.992	0.990	0.990	0.011	0.109	0.208	0.316	0.337	0.337	0.343	0.426	0.663

Note: All Romano-Wolf p-values are based on 100 replications.

Table A2.13: Romano-wolf p-values of baseline VA estimates, leisure omitted

	Ethiopia			India			Peru			Vietnam		
Leisure omitted	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.011	0.059	0.079	0.068	0.040	0.218	0.713	0.673	0.673	0.141	0.149	0.208
self-esteem	0.166	0.317	0.317	0.810	0.881	0.881	0.371	0.475	0.624	0.984	0.980	0.980
Economic work												
self-efficacy	0.114	0.287	0.356	0.212	0.149	0.267	0.282	0.267	0.555	0.353	0.574	0.733
self-esteem	0.401	0.545	0.545	0.342	0.337	0.337	0.339	0.485	0.555	0.484	0.525	0.733
Study												
self-efficacy	0.966	0.951	0.951	0.607	0.584	0.782	0.194	0.158	0.158	0.188	0.059	0.059
self-esteem	0.372	0.634	0.723	0.795	0.772	0.782	0.003	0.010	0.010	0.006	0.040	0.050
School												
self-efficacy	0.882	0.921	0.921	0.134	0.208	0.337	0.003	0.010	0.010	0.943	0.921	0.921
self-esteem	0.074	0.238	0.376	0.667	0.792	0.792	0.004	0.010	0.010	0.250	0.347	0.505
Sleep												
self-efficacy	0.386	0.525	0.535	0.203	0.446	0.446	0.912	0.822	0.881	0.762	0.772	0.980
self-esteem	0.253	0.426	0.535	0.005	0.089	0.208	0.692	0.703	0.881	0.767	0.852	0.980

Note: All Romano-Wolf p-values are based on 100 replications.

Table A2.14: Romano-wolf p-values of sex estimates, school omitted

		Ethiopia			India			Peru			Vietnam	
MALE	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.050	0.119	0.119	0.365	0.495	0.743	0.975	0.970	0.990	0.825	0.782	0.921
self-esteem	0.002	0.010	0.010	0.582	0.624	0.743	0.983	0.941	0.990	1.000	1.000	1.000
Economic work												
self-efficacy	0.267	0.347	0.347	0.028	0.129	0.139	0.266	0.337	0.525	0.655	0.663	0.871
self-esteem	0.094	0.178	0.238	0.980	0.960	0.960	0.605	0.644	0.644	0.891	0.921	0.921
Study												
self-efficacy	0.884	0.911	0.911	0.986	0.960	0.960	0.404	0.347	0.594	0.200	0.257	0.257
self-esteem	0.314	0.505	0.673	0.781	0.713	0.901	0.683	0.663	0.663	0.073	0.050	0.139
Leisure												
self-efficacy	0.977	0.980	0.980	0.165	0.139	0.248	0.202	0.149	0.257	0.369	0.564	0.663
self-esteem	0.009	0.020	0.030	0.224	0.257	0.257	0.371	0.297	0.297	0.852	0.832	0.832
Sleep												
self-efficacy	0.075	0.040	0.158	0.771	0.822	0.822	0.259	0.178	0.238	0.067	0.069	0.109
self-esteem	0.877	0.891	0.891	0.059	0.109	0.248	0.184	0.139	0.238	0.489	0.436	0.436
		Ethiopia			India			Peru			Vietnam	
FEMALE	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.175	0.307	0.446	0.007	0.030	0.030	0.095	0.040	0.079	0.051	0.040	0.079
self-esteem	0.708	0.812	0.812	0.574	0.624	0.624	0.177	0.089	0.089	0.202	0.139	0.139
Economic work												
self-efficacy	0.064	0.119	0.188	0.012	0.010	0.010	0.605	0.614	0.614	0.046	0.040	0.069
self-esteem	0.688	0.644	0.644	0.409	0.426	0.426	0.367	0.317	0.594	0.305	0.287	0.287
Study												
self-efficacy	0.842	0.911	0.911	0.686	0.614	0.832	0.735	0.832	0.832	0.703	0.673	0.891
self-esteem	0.664	0.644	0.861	0.608	0.713	0.832	0.131	0.109	0.248	0.845	0.861	0.891
Leisure												
self-efficacy	0.928	0.921	0.921	0.221	0.168	0.297	0.014	0.040	0.040	0.311	0.139	0.139
self-esteem	0.743	0.753	0.911	0.351	0.347	0.347	0.009	0.020	0.040	0.034	0.059	0.059
Sleep												
self-efficacy	0.540	0.505	0.782	0.097	0.297	0.455	0.297	0.327	0.564	0.012	0.010	0.030
self-esteem	0.907	0.931	0.931	0.148	0.386	0.455	0.855	0.871	0.871	0.017	0.040	0.040

Note: All Romano-Wolf p-values are based on 100 replications.

Table A2.15: Romano-wolf p-values of sex estimates, leisure omitted

		Ethiopia			India			Peru			Vietnam	
MALE	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.03	0.08	0.09	0.90	0.95	0.95	0.19	0.15	0.35	0.46	0.55	0.69
self-esteem	0.22	0.17	0.17	0.19	0.24	0.44	0.55	0.60	0.62	1.00	1.00	1.00
Economic work												
self-efficacy	0.27	0.45	0.45	0.92	0.95	0.95	0.59	0.60	0.80	0.68	0.83	0.99
self-esteem	0.16	0.23	0.41	0.29	0.37	0.51	0.58	0.69	0.80	0.87	0.92	0.99
Study												
self-efficacy	0.84	0.91	0.91	0.34	0.33	0.33	0.92	0.94	0.94	0.29	0.37	0.37
self-esteem	0.56	0.76	0.85	0.25	0.25	0.33	0.34	0.43	0.65	0.03	0.06	0.07
School												
self-efficacy	0.98	0.99	0.99	0.16	0.14	0.25	0.06	0.01	0.10	0.43	0.52	0.70
self-esteem	0.01	0.02	0.03	0.22	0.23	0.25	0.24	0.26	0.26	0.87	0.84	0.84
Sleep												
self-efficacy	0.06	0.08	0.16	0.70	0.83	0.83	0.78	0.75	0.75	0.19	0.22	0.25
self-esteem		0.15			0.19			0.48			0.49	
FEMALE	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.170	0.228	0.297	0.142	0.129	0.228	0.973	0.960	0.960	0.171	0.099	0.139
self-esteem	0.458	0.535	0.535	0.297	0.307	0.307	0.577	0.515	0.713	0.984	0.990	0.990
Economic work												
self-efficacy	0.059	0.129	0.158	0.399	0.307	0.307	0.495	0.574	0.792	0.506	0.555	0.683
self-esteem	0.456	0.505	0.505	0.171	0.139	0.188	0.562	0.604	0.792	0.440	0.436	0.683
Study												
self-efficacy	0.864	0.931	0.960	0.787	0.782	0.782	0.096	0.119	0.119	0.797	0.762	0.762
self-esteem	0.774	0.782	0.960	0.278	0.287	0.376	0.003	0.010	0.020	0.188	0.376	0.416
School												
self-efficacy	0.927	0.931	0.931	0.221	0.208	0.366	0.017	0.079	0.079	0.280	0.188	0.248
self-esteem	0.743	0.782	0.921	0.351	0.406	0.406	0.002	0.010	0.020	0.130	0.208	0.248
Sleep												
self-efficacy	0.556	0.693	0.891	0.252	0.416	0.416	0.725	0.762	0.762	0.046	0.010	0.040
self-esteem	0.921	0.990	0.990	0.053	0.208	0.317	0.115	0.109	0.228	0.148	0.158	0.158

Note: All Romano-Wolf p-values are based on 100 replications.

2.13 Appendix E

2.13.1 Estimates for socio-emotional skills using a latent construct

Table A2.16: Estimates for latent construct of socio-emotional skills, school and leisure omitted

	Ethiopia	India	Peru	Vietnam
	School omitted			
Domestic work	-0.054*	-0.016	-0.014	-0.016
	(0.026)	(0.023)	(0.013)	(0.017)
Economic work	-0.026	-0.024	-0.019	-0.001
	(0.021)	(0.015)	(0.017)	(0.012)
Studying outside school	-0.003	0.022	0.017	0.047
	(0.052)	(0.025)	(0.024)	(0.030)
Leisure	-0.012	-0.013	-0.050***	-0.004
	(0.026)	(0.020)	(0.015)	(0.019)
Sleep	0.017	-0.051	-0.028	-0.006
	(0.023)	(0.064)	(0.020)	(0.027)
Lagged latent score	0.097***	0.134***	0.237***	0.198***
	(0.023)	(0.023)	(0.019)	(0.034)
p-value joint test	0.195	0.020	0.015	0.021
p-value domestic = economic work	0.156	0.734	0.780	0.302
p-value study = leisure	0.837	0.247	0.004	0.020
p-value domestic work = leisure	0.113	0.922	0.069	0.603
p-value economic work = leisure	0.483	0.580	0.114	0.912
	Leisure omitted			
Domestic work	-0.042	-0.003	0.015	-0.014
	(0.025)	(0.028)	(0.016)	(0.022)
Economic work	-0.014	-0.011	0.020	0.002
	(0.019)	(0.020)	(0.018)	(0.018)
In school	0.009	0.035	0.053**	0.050**
	(0.042)	(0.029)	(0.021)	(0.021)
Studying outside school	0.012	0.013	0.047***	0.003
	(0.026)	(0.020)	(0.014)	(0.020)
Sleep	0.029	-0.038	0.006	-0.003
	(0.032)	(0.062)	(0.018)	(0.028)
Lagged latent score	0.097***	0.134***	0.231***	0.197***
	(0.023)	(0.023)	(0.019)	(0.034)
p-value joint test	0.146	0.017	0.002	0.244
p-value domestic = economic work	0.156	0.734	0.819	0.293
p-value study = leisure	0.948	0.399	0.820	0.169
p-value domestic work = leisure	0.052	0.506	0.043	0.379
p-value economic work = leisure	0.216	0.116	0.153	0.935
Observations	1,454	1,348	1,643	1,619
R-squared	0.224	0.123	0.149	0.140

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses, clustered at each country's cluster level in Round 5 (age 15). All estimates control for adolescent, caregiver and household characteristics and time allocation at age 12.

2.14 Appendix F

2.14.1 Estimates including type of school (only for those enrolled in school)

Table A2.17: Estimates controlling for type of school, leisure omitted

	Ethiopia		India		Peru		Vietnam	
	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem
Domestic work	-0.036*	-0.031	-0.008	-0.014	-0.000	0.003	-0.027	-0.014
	(0.019)	(0.018)	(0.014)	(0.020)	(0.010)	(0.012)	(0.017)	(0.017)
Economic work	-0.029	-0.000	0.009	-0.006	0.009	0.013	-0.014	-0.014
	(0.018)	(0.013)	(0.022)	(0.032)	(0.010)	(0.011)	(0.022)	(0.018)
Studying outside school	-0.012	0.009	0.011	-0.014	0.017	0.043***	0.004	0.026*
	(0.026)	(0.029)	(0.020)	(0.015)	(0.013)	(0.014)	(0.007)	(0.015)
Attending school	-0.014	0.009	0.014	-0.027	0.022**	0.021**	-0.008	0.003
	(0.026)	(0.024)	(0.018)	(0.021)	(0.009)	(0.010)	(0.016)	(0.013)
Sleep	0.009	0.024	-0.016	-0.059*	-0.005	0.003	-0.001	-0.001
	(0.023)	(0.026)	(0.037)	(0.030)	(0.010)	(0.014)	(0.012)	(0.019)
Lagged skill score	0.082**	0.087***	0.106***	0.066***	0.209***	0.203***	0.192***	0.206***
	(0.033)	(0.020)	(0.027)	(0.020)	(0.027)	(0.018)	(0.032)	(0.037)
Constant	-0.359	-0.066	-1.351	0.888	-1.098	-1.675*	-1.062	-0.377
	(0.710)	(0.722)	(0.870)	(0.835)	(0.688)	(0.807)	(0.872)	(0.605)
p-value domestic=economic work	0.689	0.023	0.573	0.857	0.510	0.532	0.367	0.977
p-value school=study	0.927	0.985	0.854	0.459	0.781	0.152	0.392	0.170
p-value domestic work=school	0.275	0.153	0.346	0.629	0.022	0.100	0.150	0.290
p-value economic work=school	0.586	0.704	0.832	0.576	0.230	0.446	0.706	0.327
Observations	1,408	1,408	1,428	1,428	1,659	1,659	1,423	1,423
R-squared	0.176	0.198	0.120	0.084	0.142	0.103	0.138	0.137

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All estimates control for adolescent, caregiver and household characteristics, lagged time allocation, as well as lagged mathematics and skill score. Standard errors are reported in parentheses, clustered at each country’s cluster level.

Table A2.18: Estimates controlling for type of school, school omitted

	Ethiopia		India		Peru		Vietnam	
	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem
Domestic work	-0.022	-0.040	-0.022	0.014	-0.015*	-0.010	-0.021*	-0.017
	(0.019)	(0.027)	(0.023)	(0.028)	(0.008)	(0.010)	(0.011)	(0.014)
Economic work	-0.014	-0.009	-0.004	0.021	-0.010	-0.004	-0.008	-0.018
	(0.025)	(0.024)	(0.020)	(0.038)	(0.010)	(0.010)	(0.015)	(0.016)
Studying outside school	0.003	0.001	-0.003	0.013	-0.002	0.025*	0.010	0.022
	(0.028)	(0.029)	(0.015)	(0.017)	(0.015)	(0.014)	(0.011)	(0.014)
Leisure	0.014	-0.009	-0.014	0.027	-0.026***	-0.026**	0.006	-0.004
	(0.026)	(0.024)	(0.018)	(0.021)	(0.008)	(0.010)	(0.014)	(0.011)
Sleep	0.023	0.015	-0.030	-0.032	-0.022*	-0.013	0.004	-0.004
	(0.016)	(0.023)	(0.036)	(0.028)	(0.011)	(0.015)	(0.014)	(0.016)
Lagged skill score	0.082**	0.087***	0.106***	0.066***	0.212***	0.203***	0.194***	0.207***
	(0.033)	(0.020)	(0.027)	(0.020)	(0.027)	(0.018)	(0.031)	(0.037)
Constant	-0.407	0.078	-1.814**	0.315	-0.751	-1.299	-0.902	-0.063
	(0.843)	(0.870)	(0.691)	(0.743)	(0.678)	(0.853)	(0.980)	(0.740)
p-value domestic=economic work	0.689	0.023	0.573	0.857	0.715	0.681	0.367	0.979
p-value school=study	0.650	0.748	0.603	0.370	0.070	0.002	0.635	0.108
p-value domestic work=school	0.066	0.973	0.568	0.859	0.346	0.051	0.148	0.488
p-value economic work=school	0.126	0.126	0.677	0.677	0.082	0.082	0.550	0.550
Observations	1,408	1,408	1,428	1,428	1,659	1,659	1,423	1,423
R-squared	0.176	0.198	0.120	0.084	0.142	0.103	0.137	0.136

Note: *** p<0.01, ** p<0.05, * p<0.1. All estimates control for adolescent, caregiver and household characteristics, lagged time allocation, as well as lagged mathematics and skill score. Standard errors are reported in parentheses, clustered at each country's cluster level.

2.15 Appendix G

2.15.1 Fixed effects estimates

Table A2.19: Fixed effects estimates, school omitted

	Ethiopia		India		Peru		Vietnam	
	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem
Domestic work	-0.021	-0.033**	-0.041***	-0.005	-0.012	0.004	-0.009	-0.008
	(0.014)	(0.015)	(0.014)	(0.015)	(0.010)	(0.011)	(0.010)	(0.010)
Economic work	0.005	-0.002	-0.027***	0.008	-0.023**	-0.009	-0.005	-0.002
	(0.012)	(0.012)	(0.009)	(0.009)	(0.010)	(0.011)	(0.007)	(0.007)
Leisure	0.018	-0.015	-0.017*	0.019**	-0.039***	-0.031***	0.005	-0.005
	(0.011)	(0.012)	(0.009)	(0.010)	(0.009)	(0.010)	(0.007)	(0.008)
Studying outside school	0.007	-0.042**	-0.039***	0.005	-0.011	0.011	0.001	0.018
	(0.019)	(0.020)	(0.015)	(0.015)	(0.014)	(0.014)	(0.011)	(0.012)
Sleep	0.047**	0.008	-0.022	0.007	-0.024*	-0.003	-0.008	-0.014
	(0.019)	(0.019)	(0.018)	(0.019)	(0.013)	(0.014)	(0.012)	(0.013)
In rural location	-0.421***	-0.321**	0.086	-0.048	-0.019	-0.030	-0.105	0.117
	(0.156)	(0.146)	(0.109)	(0.122)	(0.081)	(0.089)	(0.132)	(0.108)
Household size	0.018	0.017	0.001	-0.009	0.004	-0.002	0.008	0.019
	(0.015)	(0.016)	(0.014)	(0.014)	(0.011)	(0.012)	(0.016)	(0.015)
Adolescent's age (in months)	0.001	0.001	0.000	-0.000	-0.001	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wealth index	0.178	0.444**	0.159	0.279*	-0.136	-0.238	-0.088	-0.125
	(0.189)	(0.196)	(0.157)	(0.167)	(0.137)	(0.146)	(0.158)	(0.167)
Caregiver's education (ref: Incomplete primary or less)								
Completed primary up to lower secondary	-0.086	-0.220***	0.189*	0.075	0.004	0.047	-0.030	0.032
	(0.070)	(0.070)	(0.110)	(0.120)	(0.071)	(0.075)	(0.066)	(0.070)
Upper secondary	-0.263	-0.451	0.524	0.857***	0.024	0.023	0.002	0.325**
	(0.317)	(0.284)	(0.346)	(0.286)	(0.084)	(0.097)	(0.137)	(0.155)
Higher education	-0.136	0.004	0.349**	0.064	-0.010	-0.064	0.029	0.219**
	(0.112)	(0.119)	(0.169)	(0.177)	(0.100)	(0.120)	(0.096)	(0.110)
Height-for-age z-score	-0.001	0.013	-0.000	0.000***	-0.000*	-0.001***	0.006	-0.012
	(0.023)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.019)
Is the oldest	-0.162	0.215	-0.158	-0.171	-0.094	-0.259	0.126	-0.002
	(0.286)	(0.175)	(0.113)	(0.142)	(0.156)	(0.179)	(0.241)	(0.255)
Is the only child	-0.112	0.138	-0.245*	-0.305*	-0.086	-0.241	0.062	-0.005
	(0.300)	(0.193)	(0.135)	(0.161)	(0.159)	(0.187)	(0.250)	(0.264)
Both parents in household	0.042	0.060	0.010	0.000	-0.020	0.002	0.105	0.103
	(0.062)	(0.070)	(0.062)	(0.064)	(0.061)	(0.061)	(0.080)	(0.074)
Number of siblings	0.006	-0.081**	0.183***	0.028	0.032	0.007	0.045	-0.040
	(0.037)	(0.038)	(0.049)	(0.068)	(0.026)	(0.033)	(0.080)	(0.068)
Constant	-0.279	-0.446	-0.126	-0.004	0.169	0.021	-0.130	-0.306
	(0.756)	(0.661)	(0.357)	(0.370)	(0.240)	(0.286)	(0.390)	(0.407)
Observations	3,485	3,486	3,689	3,690	3,461	3,463	3,700	3,700
R-squared	0.037	0.044	0.034	0.027	0.019	0.016	0.017	0.022
Number of id	1,786	1,786	1,879	1,879	1,779	1,780	1,888	1,888

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses, clustered at each country's cluster level in Round 5 (age 15).

Table A2.20: Fixed effects estimates, leisure omitted

	Ethiopia		India		Peru		Vietnam	
	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem
Domestic work	-0.039***	-0.018	-0.024	-0.025	0.005	0.018	-0.015*	-0.003
	(0.012)	(0.012)	(0.015)	(0.016)	(0.009)	(0.011)	(0.009)	(0.010)
Economic work	-0.013	0.013	-0.010	-0.012	-0.004	0.006	-0.011	0.003
	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.008)	(0.008)
Attending school	-0.018	0.015	0.017*	-0.019**	0.021**	0.017*	-0.006	0.005
	(0.011)	(0.012)	(0.009)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)
Studying outside school	-0.012	-0.027	-0.022	-0.014	0.008	0.026*	-0.004	0.023**
	(0.016)	(0.017)	(0.014)	(0.013)	(0.014)	(0.014)	(0.008)	(0.010)
Sleep	0.029	0.023	-0.005	-0.012	-0.007	0.010	-0.013	-0.009
	(0.018)	(0.018)	(0.018)	(0.019)	(0.013)	(0.015)	(0.011)	(0.012)
In rural location	-0.421***	-0.321**	0.086	-0.048	-0.018	-0.029	-0.105	0.117
	(0.156)	(0.146)	(0.109)	(0.122)	(0.081)	(0.090)	(0.132)	(0.108)
Household size	0.018	0.017	0.001	-0.009	0.002	-0.003	0.008	0.019
	(0.015)	(0.016)	(0.014)	(0.014)	(0.011)	(0.012)	(0.015)	(0.015)
Adolescent's age (in months)	0.001	0.001	0.000	-0.000	-0.001	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wealth index	0.178	0.444**	0.159	0.279*	-0.119	-0.225	-0.086	-0.127
	(0.189)	(0.196)	(0.157)	(0.167)	(0.138)	(0.146)	(0.158)	(0.168)
Caregiver's education (ref: Incomplete primary or less)								
Completed primary up to lower secondary	-0.086	-0.220***	0.189*	0.075	-0.005	0.040	-0.030	0.032
	(0.070)	(0.070)	(0.110)	(0.120)	(0.072)	(0.076)	(0.066)	(0.070)
Upper secondary	-0.263	-0.451	0.524	0.857***	0.023	0.022	0.001	0.325**
	(0.317)	(0.284)	(0.346)	(0.286)	(0.086)	(0.097)	(0.137)	(0.155)
Higher education	-0.136	0.004	0.349**	0.064	-0.009	-0.063	0.028	0.219**
	(0.112)	(0.119)	(0.169)	(0.177)	(0.102)	(0.121)	(0.096)	(0.110)
Height-for-age z-score	-0.001	0.013	-0.000	0.000***	-0.000	-0.001***	0.006	-0.012
	(0.023)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.019)
Is the oldest	-0.162	0.215	-0.158	-0.171	-0.085	-0.253	0.124	-0.001
	(0.286)	(0.175)	(0.113)	(0.142)	(0.154)	(0.178)	(0.241)	(0.255)
Is the only child	-0.112	0.138	-0.245*	-0.305*	-0.082	-0.237	0.059	-0.003
	(0.300)	(0.193)	(0.135)	(0.161)	(0.157)	(0.185)	(0.250)	(0.264)
Both parents in household	0.042	0.060	0.010	0.000	-0.025	-0.002	0.105	0.102
	(0.062)	(0.070)	(0.062)	(0.064)	(0.061)	(0.061)	(0.080)	(0.074)
Number of siblings	0.006	-0.081**	0.183***	0.028	0.033	0.008	0.045	-0.040
	(0.037)	(0.038)	(0.049)	(0.068)	(0.027)	(0.033)	(0.080)	(0.068)
Constant	0.160	-0.812	-0.532	0.460	-0.328	-0.373	0.003	-0.432
	(0.730)	(0.638)	(0.358)	(0.360)	(0.248)	(0.291)	(0.388)	(0.395)
R-squared	0.037	0.044	0.034	0.027	0.011	0.012	0.017	0.022
Number of id	1,786	1,786	1,879	1,879	1,779	1,780	1,888	1,888
Observations	3,485	3,486	3,689	3,690	3,461	3,463	3,700	3,700

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are reported in parentheses, clustered at each country's cluster level in Round 5 (age 15).

2.16 Appendix H

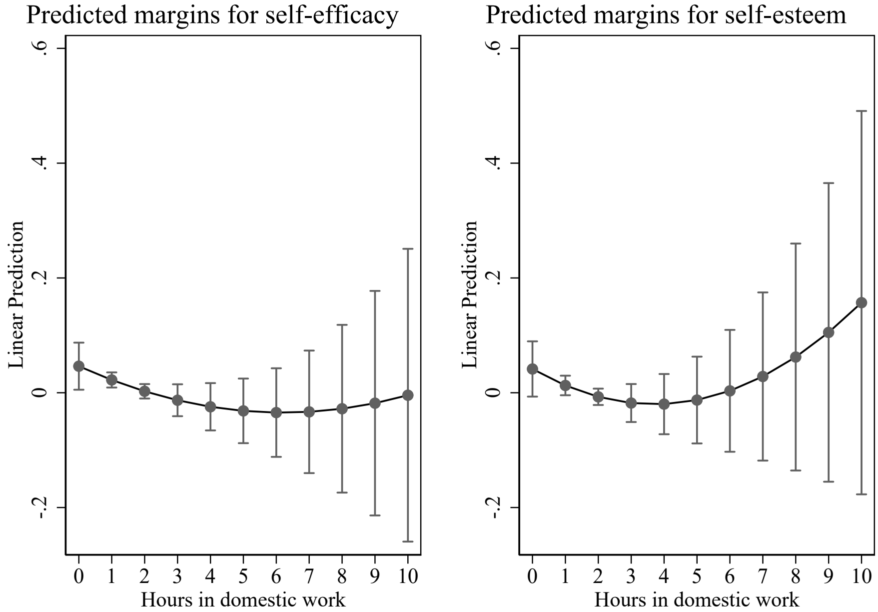
2.16.1 Linearity in estimates

Table A2.21: Estimates using squared hours in domestic and economic work (school omitted)

	Ethiopia		India		Peru		Vietnam	
	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem	Self-efficacy	Self-esteem
Domestic work	-0.062**	-0.077***	-0.015	0.013	-0.018	-0.012	-0.026	-0.033*
	(0.028)	(0.024)	(0.031)	(0.026)	(0.013)	(0.014)	(0.016)	(0.019)
Domestic work (squared)	0.004	0.005**	-0.004	-0.001	0.001	0.001	0.002	0.004
	(0.003)	(0.002)	(0.005)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)
Economic work	-0.039	-0.016	-0.044	-0.003	-0.009	-0.016	-0.048**	-0.049**
	(0.031)	(0.024)	(0.028)	(0.031)	(0.026)	(0.022)	(0.021)	(0.019)
Economic work (squared)	0.002	0.000	0.002	-0.000	-0.000	0.001	0.004**	0.005**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Leisure	-0.008	-0.025	-0.011	0.004	-0.025***	-0.028***	-0.001	-0.012
	(0.019)	(0.018)	(0.010)	(0.011)	(0.008)	(0.009)	(0.009)	(0.009)
Study outside school	-0.006	-0.005	-0.003	0.001	0.001	0.027*	0.009	0.017
	(0.031)	(0.033)	(0.013)	(0.013)	(0.015)	(0.013)	(0.012)	(0.014)
Sleep	0.008	-0.001	-0.037	-0.049**	-0.021	-0.014	-0.005	-0.014**
	(0.012)	(0.018)	(0.033)	(0.025)	(0.012)	(0.014)	(0.014)	(0.016)
Observations	1,551	1,551	1,756	1,756	1,698	1,698	1,695	1,695
R-squared	0.181	0.192	0.131	0.071	0.143	0.106	0.132	0.126

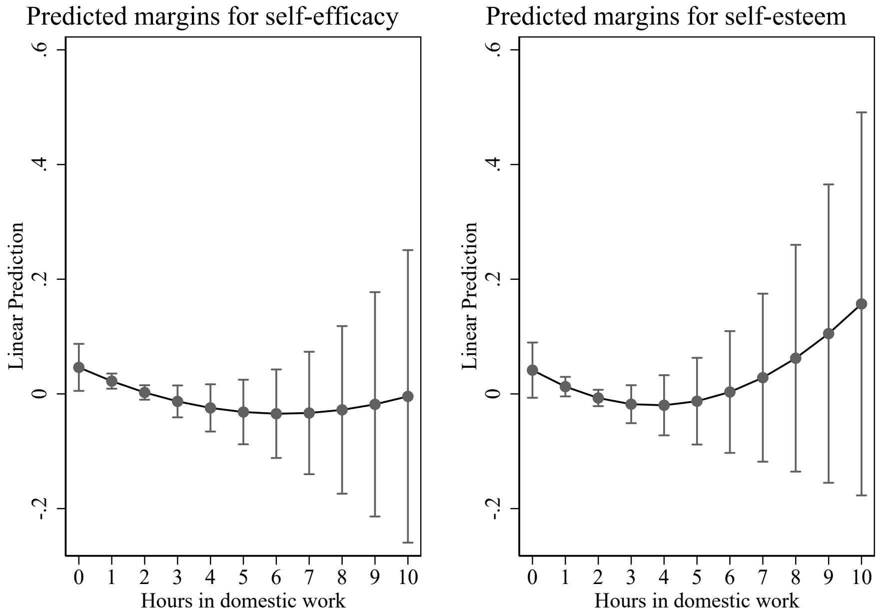
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All estimates control for adolescent, caregiver and household characteristics, lagged time allocation, lagged mathematics scores, as well as lagged self-esteem or self-efficacy scores as per the extended VA model. Standard errors are reported in parentheses, clustered at each country's cluster level.

Figure A2.1: Predicted margins in Vietnam with increasing hours of domestic work



Note: Plotted predicted margins for generalised self-efficacy with increasing hours of domestic work in Vietnam. This figure plots column (1) in Table A2.21 for Vietnam. The turning point is 5.87.

Figure A2.2: Predicted margins in Vietnam with increasing hours of economic work



Note: Same as Figure A2.1 but for economic work. The turning point is at 5.52 hours.

2.17 Appendix I

2.17.1 Estimates by locality

Table A2.22: Estimates for generalised self-esteem by locality, school omitted

	Ethiopia		India		Peru		Vietnam	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Self-esteem								
Domestic work, age 15	-0.031	-0.045**	-0.012	0.057*	-0.022	-0.005	-0.007	-0.002
	(0.018)	(0.027)	(0.016)	(0.025)	(0.022)	(0.012)	(0.014)	(0.019)
Economic work, age 15	-0.011	-0.023	-0.003	-0.028**	0.005	-0.030*	-0.003	0.008
	(0.016)	(0.022)	(0.006)	(0.007)	(0.018)	(0.007)	(0.008)	(0.010)
Studying outside school	-0.017	-0.004	0.007	-0.005	0.044	0.025	0.031*	0.012
	(0.039)	(0.051)	(0.015)	(0.030)	(0.043)	(0.014)	(0.017)	(0.017)
Leisure, age 15	-0.019	-0.029	-0.005	0.013	-0.025	-0.031**	-0.009	0.005
	(0.016)	(0.027)	(0.011)	(0.021)	(0.022)	(0.011)	(0.010)	(0.014)
Sleep, age 15	-0.017	0.013	-0.039	-0.073*	-0.034	-0.014	-0.014	-0.002
	(0.026)	(0.038)	(0.031)	(0.039)	(0.039)	(0.017)	(0.020)	(0.021)
Self-esteem, age 12	0.063**	0.092	0.039	0.105**	0.233***	0.195***	0.143***	0.334**
	(0.026)	(0.054)	(0.026)	(0.043)	(0.044)	(0.022)	(0.025)	(0.092)
Constant	0.568	-0.306	0.629*	0.300	-0.720	-0.426	-0.202	-0.064
	(0.502)	(0.319)	(0.332)	(0.603)	(0.544)	(0.295)	(0.382)	(0.617)
R-squared	0.230	0.114	0.066	0.146	0.179	0.107	0.101	0.224
domestic=economic work	0.042	0.225	0.633	0.007	0.433	0.072	0.757	0.565
study=leisure	0.961	0.454	0.592	0.563	0.063	0.001	0.029	0.582
domestic work=leisure	0.457	0.563	0.722	0.214	0.892	0.133	0.908	0.579
economic work=leisure	0.573	0.771	0.896	0.065	0.224	0.941	0.608	0.832
Self-efficacy								
Domestic work, age 15	-0.026	-0.037**	-0.067**	0.019	-0.024	-0.017	-0.008	-0.031*
	(0.017)	(0.019)	(0.017)	(0.024)	(0.026)	(0.009)	(0.009)	(0.007)
Economic work, age 15	-0.015	-0.015	-0.028**	-0.019**	-0.015	-0.019	-0.004	-0.012
	(0.014)	(0.015)	(0.011)	(0.006)	(0.014)	(0.014)	(0.008)	(0.010)
Studying outside school	0.010	-0.019	-0.007	-0.007	-0.004	0.007	0.026*	-0.019
	(0.041)	(0.037)	(0.020)	(0.023)	(0.033)	(0.016)	(0.012)	(0.012)
Leisure, age 15	0.010	-0.018	-0.030**	0.008	-0.037	-0.033**	0.005	-0.011
	(0.014)	(0.028)	(0.010)	(0.017)	(0.023)	(0.008)	(0.011)	(0.010)
Sleep, age 15	0.016	0.003	-0.013	-0.122**	-0.017	-0.031	0.009	-0.050*
	(0.018)	(0.026)	(0.035)	(0.038)	(0.032)	(0.014)	(0.017)	(0.013)
Self-efficacy, age 12	0.075**	0.098	0.122***	0.132**	0.268***	0.208***	0.155***	0.230***
	(0.032)	(0.058)	(0.034)	(0.042)	(0.050)	(0.037)	(0.038)	(0.008)
Constant	0.098	0.253	0.156	0.885*	-1.035*	0.093	0.045	0.499
	(0.379)	(0.256)	(0.409)	(0.441)	(0.572)	(0.270)	(0.451)	(0.938)
R-squared	0.230	0.089	0.130	0.184	0.214	0.111	0.136	0.215
p-value domestic=economic work	0.408	0.304	0.0384	0.202	0.754	0.880	0.568	0.0946
p-value study=leisure	0.994	0.975	0.301	0.660	0.271	0.0139	0.00196	0.605
p-value domestic work=leisure	0.0127	0.522	0.0383	0.736	0.544	0.219	0.403	0.0457
p-value economic work=leisure	0.0716	0.907	0.850	0.111	0.342	0.370	0.495	0.921
Observations	995	556	1,223	533	425	1,273	1,353	342

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All estimates control for adolescent, caregiver and household characteristics, lagged time allocation, as well as lagged mathematics and self-esteem scores. Standard errors are reported in parentheses, clustered at each country's cluster level.

Table A2.23: Romano-wolf p-values of locality estimates, school omitted

	Ethiopia			India			Peru			Vietnam		
RURAL	Model	Resample	Romano-Wolf	Model	Resample	Romano-Wolf	Model	Resample	Romano-Wolf	Model	Resample	Romano-Wolf
Domestic work												
self-efficacy	0.098	0.158	0.158	0.000	0.010	0.010	0.555	0.644	0.644	0.371	0.248	0.525
self-esteem	0.040	0.069	0.149	0.476	0.495	0.495	0.305	0.337	0.515	0.630	0.703	0.703
Economic work												
self-efficacy	0.110	0.149	0.228	0.001	0.010	0.010	0.301	0.188	0.337	0.556	0.545	0.753
self-esteem	0.327	0.436	0.436	0.723	0.654	0.654	0.385	0.347	0.347	0.677	0.654	0.753
Study												
self-efficacy	0.971	1.000	1.000	0.784	0.772	0.782	0.806	0.901	0.901	0.090	0.030	0.069
self-esteem	0.426	0.545	0.683	0.691	0.584	0.782	0.129	0.396	0.446	0.050	0.069	0.069
Leisure												
self-efficacy	0.631	0.525	0.525	0.009	0.010	0.020	0.065	0.139	0.158	0.601	0.743	0.743
self-esteem	0.153	0.158	0.238	0.686	0.624	0.624	0.370	0.386	0.386	0.259	0.396	0.545
Sleep												
self-efficacy	0.487	0.347	0.564	0.955	0.970	0.970	0.308	0.446	0.673	0.576	0.525	0.525
self-esteem	0.406	0.465	0.564	0.105	0.267	0.376	0.372	0.584	0.673	0.288	0.376	0.475
	Ethiopia			India			Peru			Vietnam		
URBAN	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf	Model	Resample p-val	Romano-wolf
Domestic work												
self-efficacy	0.085	0.030	0.040	0.373	0.366	0.366	0.216	0.129	0.317	0.217	0.010	0.059
self-esteem	0.036	0.030	0.040	0.045	0.059	0.079	0.606	0.614	0.614	0.934	0.822	0.822
Economic work												
self-efficacy	0.462	0.317	0.317	0.351	0.050	0.040	0.158	0.188	0.188	0.608	0.277	0.277
self-esteem	0.227	0.178	0.248	0.174	0.020	0.030	0.023	0.010	0.050	0.462	0.099	0.248
Study												
self-efficacy	0.552	0.525	0.772	0.884	0.871	0.960	0.981	0.990	0.990	0.485	0.208	0.386
self-esteem	0.921	0.960	0.960	0.797	0.782	0.960	0.330	0.168	0.436	0.821	0.693	0.693
Leisure												
self-efficacy	0.298	0.416	0.416	0.411	0.327	0.525	0.022	0.010	0.020	0.596	0.307	0.545
self-esteem	0.110	0.149	0.267	0.305	0.396	0.525	0.020	0.020	0.020	0.672	0.495	0.545
Sleep												
self-efficacy	0.878	0.713	0.733	0.001	0.010	0.010	0.122	0.050	0.139	0.098	0.040	0.050
self-esteem	0.616	0.683	0.733	0.071	0.079	0.079	0.380	0.446	0.446	0.787	0.762	0.762

Note: All Romano-Wolf p-values are based on 100 replications.

Chapter 3

How is university students' paid work associated with their locus of control?

Abstract

This study examines whether university students doing paid work during their studies improves their internal locus of control – the belief in one's ability to have control over their life events. Using longitudinal data on a cohort of English students, I estimate a standard skill production function and control for lagged locus of control and a rich set of covariates to partially account for unobserved heterogeneity and selection into paid work. The findings show that engagement in paid work, rather than hours spent in work, is associated with greater students' internal locus of control. Students who ever worked during university had 0.08 standard deviations more internal locus of control than students who do not work, and these estimates are largely relevant for term-time work. Estimates during the holidays are smaller in magnitude and statistically insignificant. I do not find any non-linearities in hours of work to skills development, nor do I find heterogeneities by gender. The findings show support for the human capital theory that work experience can help facilitate skills development.

This chapter is published at the Research in Social Stratification and Mobility as Chang (2023) and edited according to the examiners' feedback

3.1 Introduction

Many students are often faced with a cost-benefit decision regarding whether to work while studying. Nearly two-thirds of tertiary students engage in work in countries such as England and Northern Ireland, Canada, and Germany (Quintini 2015). On the one hand, the human capital theory predicts that working while studying may help students gain transferable skills such as social skills, confidence, and social networks (G. S. Becker 1964). On the other hand, the zero-sum theory predicts that work competes with students' time for more productive activities, such as their academic responsibilities, leading to poorer academic achievement. Existing empirical research has focused on the latter relationship, and on average has found a neutral or detrimental association between student work and academic performance in tertiary education (See Neyt et al. (2019) for a review). However, studies have found that student employment can be beneficial for later labour market success such as higher wages, greater employability and lower unemployment risk, especially if the work is related to their university subject (Geel and Backes-Gellner 2012). While there is evidence that suggests advantages of university student employment, it remains less explored whether these advantages are achieved through the acquisition of transferable skills from work. In particular, there is a gap in the empirical literature relating students' paid work and socio-emotional competencies, which is important since socio-emotional competencies have been shown to be learnable, and positively influence adult economic outcomes such as earnings and occupational choice (Heckman, Jagelka, and Kautz 2021; Almlund et al. 2011; Heckman, Stixrud, and Urzua 2006).

This paper fills this gap by examining whether university students who do paid work during their studies have higher internal locus of control (LOC) than students who do not. LOC is a socio-emotional skill that measures the belief in one's ability to have control over the events in (one's) life. Individuals with an internal LOC believe that their individual actions and internal qualities are responsible for their life outcomes. Conversely, an external LOC is the belief that life outcomes are due to external factors such as chance and luck (Lefcourt 1991). LOC is widely studied in Economics and Psychology, and is found to be as important as cognitive ability in predicting future outcomes (Heckman, Stixrud, and Urzua

2006), such as earnings (Piatek and Pinger 2016; Heineck and Anger 2010), unemployment (Caliendo, Cobb-Clark, and Uhlendorff 2010), educational attainment (Piatek and Pinger 2016), and the ability to cope with health shocks (Schurer 2017). Importantly, research find that LOC can be shaped by life events Stillman and Velamuri (2020), and working during university may be an important life event, especially since previous research show that employment can lead to more internal LOC (Gottshalk 2005). While it is beyond the scope of this paper to champion internal LOC as a desired skill, it is an established measured socio-emotional skill, which can provide a glimpse into the wider skills associated with student employment that are not captured by academic scores.

My study’s main contribution is by providing new empirical evidence about the associations between paid work during university and LOC, rarely studied before. In examining this relationship, I pose four research questions. First, is engagement in paid work positively associated with more internal LOC? If the human capital theory prevails more than the zero-sum theory, then I would expect a positive association between work and LOC. If instead there is the reconciliation approach where students are able to manage work and studies, there may be neutral associations with students’ LOC. Second, do these associations differ depending on the period in which the work is performed (i.e., term-time or the holidays)? Students who work during term-time may find greater competition between their time at work and studies, compared to work during the holidays. Students may also participate in different kinds of work during the term or the holidays. Third, is excessive hours spent in paid work associated with lower LOC? Excessive hours of work may lead to stress and fatigue, as per the zero-sum theory, and I expect that students who work excessively may have more external LOC. Fourth, how do these relationships differ by sex since male and female students have different preferences over university subjects, time management, and job choice? These research questions are relevant in understanding the costs and benefits to student employment, which may be helpful in designing policy if more disadvantaged students are engaging in paid work.

In addition, my findings add to the evidence base on university student employment in England, about which less is known because of the focus on North America (see Neyt et al. (2019)). The main reason for the few empirical studies on this issue in the United Kingdom (UK) is data limitations: information about university and higher education students' work experiences is not often collected in detail in standard household or cohort surveys. Empirical evidence in the UK comes from either cross-sectional data (Callender 2008) or from samples of students in a handful of universities (Humphrey 2006; McVicar and McKee 2002), which makes it difficult to generalise the findings beyond the specific university.

Using data from Next Steps (NS), a longitudinal study of individuals born in 1990/91, I model university students' LOC production at age 20/21 based on the student and students' family inputs across their life cycle. The data provides measures of LOC before university entry and at age 20/21, allowing me to use value-added models to control for unobserved ability and heterogeneity by using lagged LOC measures. Yearly longitudinal information between the ages of 14/15 and 20/21 further enables me to control for students' socio-economic status, attitudes, and university subject choice, all of which may affect their choice to work during university. The analyses address a selection of observables, and reduce as much as possible the unobserved heterogeneity, but a possibility of selection in terms of the unmeasured characteristics remains.

I find that students who engage in paid work during term-time have 0.12 standard deviations more internal LOC than students who do not work. My estimates remain significant and positive when including university subject indicators to account for the simultaneity between LOC and university subject choice, as well as controlling for previous determinants of work before university. However, my coefficient estimates for paid work during the holidays are smaller and statistically insignificant. I also do not find any statistically significant association from additional hours of paid work in term-time or in the holidays. Therefore, it is engagement in paid work, rather than average hours spent in paid work, which is positively associated with students' internal LOC. Paid term-time work is associated with greater LOC for female students compared to male students (0.18 standard deviations compared to 0.05 standard deviations), and this result is statistically significant at the 1% level, holding all else constant.

3.2 Working university students in the UK

Doing paid work during studies is commonplace in UK Higher Education. In 2012, almost half of tertiary students in England and Northern Ireland worked, compared to other European countries, such as Spain, where the figure was 30%, and Italy, where it was below 20% (Quintini 2015). Studies in the early 1990s found that 25% - 29% of full-time English students were doing paid work during term-time (Ford, Bosworth, and Wilson 1995). In 2014/15, Maher et al. (2018) found that 52% of full-time higher education English students did some form of paid work during the academic year. The average working hours of students who worked were 10.3 working hours per week, with the resulting income having contributed about 10% of students' higher education finances.

The rising number of UK students working during term-time has been attributed to shifts in costs from the state to students, such as the introduction of student loans in 1990 (Callender 2008; Metcalf 2003), the introduction of university tuition fees of £1,000 a year in 1998 and subsequently £3,000 a year in 2006 and £9,000 a year in 2012 (Hubble and Bolton 2018). Callender (2008) argued that between 1988/99 and 2004/05, there was not only a rise in students' employment, but also a rise in students' reliance on their wages (a rise of 14% to 22% of total income). In 2014/15, Maher et al. (2018) find that paid work was the third largest contributing source of income for students, after student loans and maintenance and education-related grants. Ongoing higher education policy changes, such as the most recent replacement of maintenance grants with loans in 2016/17 (Bolton 2022) along with rising cost of living which put pressures on student finances (Office for National Statistics, 2022), may further incentivise students to work whilst at university.

Empirical research on tertiary student employment in the UK are limited to a handful of studies with the majority of studies having found that work worsens students' academic outcomes. Humphrey (2006) and Metcalf (2003) used surveys of a small selected numbers of universities in England, and found that students who work term-time in England tended to have lower academic achievements measured by grades and probability of graduating. Callender (2008) used surveys that were more representative of universities in England, and controlled for students' prior ability (e.g., A-Levels scores) and found that students' term-time work worsens students' academic performance. In contrast, McVicar and McKee (2002) used a cohort of young people first eligible to leave school in Northern Ireland in 1993 found that part-time employment does not harm students' examination performance, as long as the student was not working more than 15 hours a week.

3.3 Theory, potential mechanisms, and prior literature

3.3.1 Theories about students' paid work and their outcomes

Studies generally agree that individuals' socio-emotional skills tend to change most strongly before working age, after which they become more consistent (Elkins, Kassenboehmer, and Schurer 2017; Cobb-Clark 2015; Terraciano, McCrae, and Jr. 2010). Using a nationally representative longitudinal data from Australia, Elkins, Kassenboehmer, and Schurer (2017) found that most changes in the Big-Five and LOC over eight years occurred between adolescence and young adulthood (age 15 – 24). Using the same data, Kassenboehmer, Leung, and Schurer (2018) showed that the university experience can help students build socio-emotional skills, namely extraversion and agreeableness, especially for students from disadvantaged backgrounds. The university experience is also unique in comparison to compulsory schooling, as university students tend to exert more autonomy over how they manage their time (i.e., whether or not to engage in paid work), and attending classes or club activities are discretionary.

Most theories on student employment are related to academic achievement and progress, but can be used to help explain their relationship with socio-emotional skills. The first theory is the human capital theory (G. S. Becker 1964), which posits that work experience allows the acquisition of new general and transferable skills such as work values, communication skills and a sense of time management (Buscha et al. 2012; Rothstein 2007; Mortimer 2003). Work experience may improve skills that in turn improve socio-emotional skills, or directly relate to improved socio-emotional skills. If this theory holds, then we can expect to see that engagement in work raises LOC.

The second is the zero-sum theory, which supposes that employment puts strong constraints on time use. Time spent in work decreases time spent on other productive university experiences such as study time (Bozick 2007) and leads to lower participation in lectures and club activities (Marsh 1991), both of which may reduce students' identification with the 'student role'. In a study of 15-year-olds, also using the Next Steps Study in the UK, Holford (2020) shows that employment at age 15 crowds out study time and motivation for school work, and reduces exam performance. Additionally, an overcommitment to paid work could result in psychological stress and anxiety (Robotham 2008), leading to poorer behaviours such as excessive drinking (Apel et al. 2008; Butler, Dodge, and Faurote 2010; Holford 2020). If this theory holds, then we will see that engagement in work instead reduces LOC.

Third is a theory directly against the zero-sum theory, called the reconciliation approach. Students may instead manage their time wisely (Dundes and Marx 2006). Engagement in work does not equate to excessive hours spent in work. While there is no empirical evidence regarding non-academic outcomes, studies on academic outcomes support this theory for tertiary students in the USA (Darolia 2014), Northern Ireland (McVicar and McKee 2002), and high school students in the USA (Kalenkoski and Pabilonia 2009) and the UK (Holford 2020). Holford (2020) found that teenage part-time work can lead to higher earnings and likelihood of employment in adulthood, but this is offset by reduced education inputs. In a study of Scottish high school students, Howieson et al. (2012) found that students did not engage in part-time work at the cost of educational engagement, or activities outside of school. The authors argue that there may be 'active students' who can engage in work and maintain their school and social activities. If this theory holds, we may see small or not statistically significant associations between paid work and LOC.

Lastly is the 'primary orientation theory' which discusses the issue of selection into paid work (Neyt et al. 2019). Students who take up employment may be prone to do worse in the measured outcomes because they put less priority in these outcomes (e.g., are less academically motivated and thus have poorer academic outcomes). This can be extended more generally that students who are more likely to engage in work may also exhibit different characteristics (e.g., stronger work ethic) to students who do not work, which may directly relate to their, say, socio-emotional skills. Therefore, it is important to consider students' characteristics that allow the student to be more prone to doing paid work.

3.3.2 Previous empirical evidence

Studies about high school student employment have found that work experience is associated with positive behaviour attitudes, the development of life skills, and future wealth (Mortimer 2003; Painter II 2010; Cunnien, Rogers, and Mortimer 2009; Lesner et al. 2018). Lesner et al. (2018) showed that part time work for Danish school students aged 15-16 improved their grade point average, enrollment in upper secondary education, and also reduced juvenile delinquency. Using longitudinal data on high school students in the USA, Cunnien, Rogers, and Mortimer (2009) found that student employment was associated with greater economic and non-economic self-efficacy, i.e., the belief in one's ability to reach a goal. The authors also found that students who work for a longer period (they term as 'steady work') but limited to 20 hours a week or less, had greater self-efficacy than students who did sporadic work. Similarly, Painter II (2010) using longitudinal data of high school students in the USA between 1985 and 2004 found that work experience was associated with greater wealth accumulation in early adulthood, and students who worked for the longest period (more than 6 months) were associated with the most wealth.

For tertiary educated students, studies relating student work experience and non-academic gains are measured through adult labour market outcomes. Geel and Backes-Gellner (2012) found that Swiss students who worked in jobs related to their field of study in university experience higher wage effects, lower unemployment risk, shorter job-search duration and greater job responsibility. Passaretta and Triventi (2015) studied student employment in four European countries and showed that any form of student employment during higher education in Italy and Spain raises future employability, with slightly more returns if the job is related to their subject studied. Using data on German graduates of 1997, Weiss, Klein, and Grauenhorst (2014) demonstrated that students' work experiences provide positive returns to their wages and social class position five years after graduation but only if they were engaged in work related to their subject of study.

There is limited evidence on the direct relationship between employment and LOC.

The most relevant study to date is by Gottshalk (2005), who used data from a randomized control trial in Canada, with the aim of determining the impact of an earnings supplement to reduce welfare recipient reliance on income assistance, using a random sample of single parents. The treated group were offered an earnings subsidy, if they worked at least 30 hours a week in an eligible job (increasing their incentive to work). He found that an exogenous increase in work hours from the experiment raised the internal LOC tendencies among welfare recipients, especially for individuals aged 30 years and below. While Gottschalk's work provides causal evidence, his study is limited to welfare recipients of single parents.

All these studies point to a link between employment and non-academic benefits, mainly showing some evidence for the human capital theory. However, evidence about work and socio-emotional skills formation are still limited, especially for students in higher education.

3.3.3 Differences by gender and period of work

There may be heterogeneities in these relationships by two main characteristics; students' gender and when the job was performed. Female and male students may have different expectations regarding labour force participation, and expected returns on university (Goldin 2006). Holford (2020) found that teenage employment had different effect sizes on educational retention, progression and labour market performance by sex, explained by stronger overall performance levels of girls at age 16, as well as job preferences. According to the author, girls were more likely to participate in retail and catering jobs while boys were more likely to participate in delivery, and the former types of jobs are more likely to promote cognitive skills such as financial literacy, mental arithmetic, and inter-personal skills that have long-run educational and labour market returns.

At the university level, subject choice by gender may also determine students' ability to work part-time. Studies have found that female and male students are less likely to choose Science, Technology, Engineering and Mathematics subjects, and have different preferences when choosing their subject (Quadlin 2020). Quadlin (2020) showed that even when female and male students end up choosing highly divergent college subjects despite citing similar preferences. There may also be gendered time preferences and attitudes. For example, Howieson et al. (2012) found that during compulsory schooling, girls were more likely to be in part-time employment than boys. While not conclusive, they suggest that boys are less motivated to undertake part-time employment, possibly due to the contested time with their hobbies or sports, compared to girls. While I do not observe types of work, examining these relationships by sex may uncover any gender differentials in student employment at the university-level.

The period when the student does paid work matters for their skills development for two reasons. First, work during term-time competes with more academic and social commitments than work during the holidays, making the zero-sum theory more relevant during term-time compared to the holidays. Second, students may engage in different types of employment during term-time and the holidays, because of these time commitments. Evidence for which period which work is performed is still inconclusive. Darolia (2014) found that paid work is adverse for full-time students' academic outcomes but not for part-time students, providing support for the zero-sum theory. In contrast, Baert et al. (2022) showed that the negative effect of paid work during secondary school on education was cancelled out by a higher chance of being employed three months after leaving school. The authors found that students who worked both during term-time and in Summer, compared to those who only worked in Summer, were more employable.

3.4 Data and variables of interest

3.4.1 The Next Steps survey

I use data from the main survey of Next Steps (NS), a longitudinal study run by the Centre for Longitudinal Studies, which followed a cohort of 15,770 young people born in England between 1st September 1989 and 31st August 1990. The NS sample is drawn from young people aged 14/15 attending state schools, private schools and alternative schools in England.[1] I use the first seven waves of information, where the young people were interviewed

[1] Private schools are schools that charge fees to attend instead of being funded by the government. What I refer to as alternative schools are called pupil referral units, which are alternative education providers in the

annually from 2004 to 2010, at the ages of 14/15 to 20/21, where the initial sample of 15,770 reduced to 8,682.

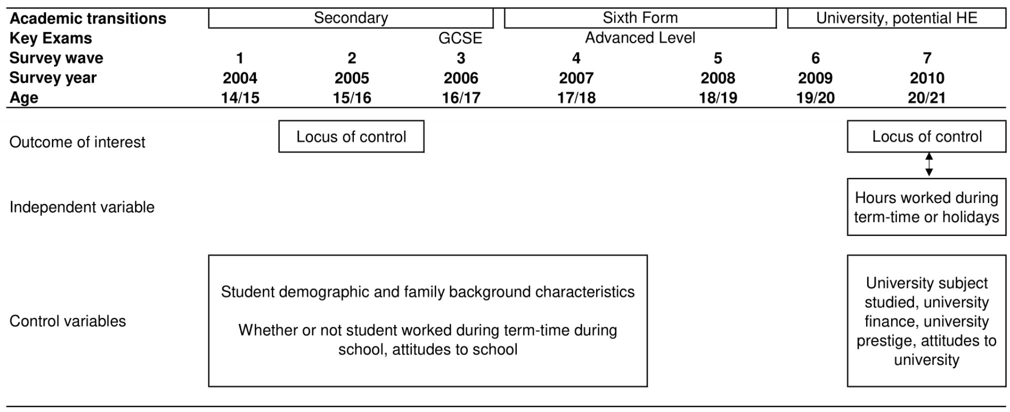
I focus solely on university students which is an unweighted sample of 3,543. Since I am focusing only on students who attended university, my analysis does not account for students who started university after 2010, or were unable to attend university. This likely means I am examining these relationships for those who follow a "standard pathway" to university. Since this sample only examines university students, it may be that these students in this sample overall have quite high LOC, as students who tend to attend university are more likely to come from wealthier socio-economic backgrounds.

The structure of the data and my variables of interest are shown in Figure 3.1. My main variables of interest – university students' participation in paid term-time work and their LOC – are from wave 7 at age 20/21. Wave 7 provides the greatest observations of university students in the data, because a third of the students in the sample deferred their entry to university or took a gap year in wave 6. By wave 7, the majority of the university students were in their second undergraduate year, and a third of them were in their first year. Using case-wise deletion to restrict my sample to full-time university students with complete information reduces my unweighted sample of interest from 3,543 to 2,426 students, but all statistics are based on probability-weighted observations, using weights in wave 7 to account for attrition bias and demographic changes between waves 1 to 7, as described in the Next Steps User Guide. The main source of missingness is from respondents answering 'Don't know' to the LOC items in wave 2 (see sub-section 3.4.2 below for further explanation).

The data provide rich university-related information and students' demographic and family background characteristics from waves 1 to 4. I also have students' previous LOC score in wave 2, which is the only available lagged LOC used as a proxy for student ability, used in the value-added model which I will discuss later in my empirical strategy.

UK, which are specifically organised to provide education to children who are not able to attend a mainstream school and may not otherwise receive suitable education.

Figure 3.1: Variables of interest in the Next Steps data



Note: Author’s own illustration based on the Next Steps, Sweeps 1 – 8, 2004-2016 data University College London (2021)

3.4.2 Locus of control

The LOC measure I use is defined in the NS data based on four statements that are similar to Gottshalk (2005): i) If someone is not a success in life, it is usually their own fault ii) I can pretty much decide what will happen in my life iii) If you work hard at something, you’ll usually succeed iv) How well you get on in this world is mostly a matter of luck. Each young person was asked to respond to these statements with levels of agreement ranging from “Strongly agree” to “Strongly disagree”. If the response indicates greater agreement with statements (i) – (iii) and a greater disagreement with statement (iv), then the individual has a greater internal LOC. The converse indicates a more external LOC. I dropped responses coded as “Don’t Know” and “Refused to answer”, which accounted for about 5% of the responses in wave 7 and 20% of the responses in wave 2. Appendix Table A3.9 shows reassuringly that there are few differences between the sample with and without including these “Don’t know” responses, except that those who were excluded were more likely to work during Summer and Easter, white, and male. Later in the paper, I show how my estimates remain consistent regardless whether “Don’t Know” is included or not.[2]

[2]Multiple imputation estimations in Appendix Table A3.15 will also show, later, that findings are similar, but with greater statistical power.

As seen in Figure A3.1 and Figure A3.2, compared to wave 2, university students in wave 7 are more likely to disagree (and less likely to agree) to the statement 'Fault' and 'Decide', and more likely to agree to the statement 'Luck'. Overall, there is a slight fall in internal LOC between waves 2 and 7. 20% of university students did not have a change in their LOC, 22% had greater internal LOC, and 58% had more external LOC. Figure A3.1 shows that the majority of students in my sample have a more internal LOC score because the majority responded "Agree" to statements (ii) and (iii) and "Disagree" to statement (iv). Therefore, the variations in score range between becoming more or less internal, rather than a movement between internality and externality.

To construct the LOC score, I first reverse-coded items 1, 2 and 3 such that all the scales indicated an internal LOC with increasing agreement. I then use exploratory factor analysis to create the final score. It is a statistical method that identifies a latent construct (e.g., LOC) underlying a set of measured variables (e.g., each statement) with different 'factor loadings' i.e., each measured variable is given a weight that best 'loads' onto the latent construct. This method is argued to have less measurement error compared to using a sum score where all items are equally weighted (Piatek and Pinger 2016).[3]

The factor analysis revealed that the factor loading of the item "luck" was very low, hence I constructed the LOC score without this item (see Appendix Table A3.1 for all factor loadings). The factor loadings for the other items (i) - (iii) were 0.4, 0.5, and 0.4 respectively and the raw correlations between both scores were 0.3. I then standardized the score for ease of interpretation. By treating the LOC measure as a continuous score, I assumed that the change between each unit was equivalent (i.e., a change between 1 and 2 was the same as a change between 2 and 3). Later in Section 3.7, I show that using a continuous sum score does not change the sign or statistical significance of my baseline estimates.

[3]Factor analysis, however, is designed to capture a construct that is arrived at through intuitive considerations and correlations among the underlying items, and may not necessarily validly predict real world outcomes. Here, I use factor analysis to examine whether the data collected are correlated to the theoretical construct of interest.

3.4.3 Measures of work

I measure students' engagement in paid work as a dichotomous measure equal to 1 if the student was doing paid work during term-time or the holidays, and 0 otherwise. Students' work hours are measured as their reported average weekly hours worked if they were doing paid work, and zero if they were not doing paid work. I also examine whether the student had ever worked i.e., worked during term-time or in any of the holiday period. However, I cannot estimate the hours worked for those 'ever worked' since work hours are reported for each period, which can differ substantially across periods.

Ideally, I would like to observe these measures during university term-time and during the holidays. However, a questionnaire routing error in the NS data means that students who currently had a job and were interviewed during their term-time were not asked about their previous employment history during Christmas or Summer (see Appendix Figure A3.3 for full details). In other words, I observe all responses about whether the student was working in term-time or Summer, but only observe partial information about students who worked in Christmas or Easter. Observing the larger sample of students overstates the number of students who worked during term-time *only*.

For my main estimates, I use the largest non-missing sample for the ever worked, term-time and Summer estimates (n=2,426), and the most restrained sample for the Christmas and Easter estimates (n=2,230). I later show that my estimates remain similar using the most restricted sample, except that there is less statistical power from the reduced sample size.

3.4.4 Additional covariates

To control for observed individual-level differences that may determine work engagement and LOC at age 20/21, I use a set of student-specific controls which are demographic characteristics such as sex, ethnicity, and whether they have any long-term health/disability. I control for whether or not they receive financial help (a grant or bursary) for university costs as less advantaged students may need to work, their attendance at a Russell Group University as university prestige my determine the academic contact hours (e.g., Oxford and

Cambridge strictly limit the hours students can engage in work compared to other universities), and whether or not they enrolled in university at wave 6, which means they are second year undergraduates and their academic burden may differ to first year undergraduates. I use a set of family background characteristics to control for early socio-economic status, which are whether the main parent has higher education, whether the main parent is a lone parent, and the number of siblings.

In order to examine potential issues regarding selection into work, I control for an additional two sets of covariates. First is whether or not the student studied a science subject, as classified by the UK Higher Education Statistics Agency (HESA). This is because of several reasons. Students who do science subjects (e.g., Medicine) may have less flexibility to work than students in non-science (e.g., Business and Administrative studies) because of greater contact hours such as time spent in the laboratory. Science subject students may also be less able to engage in relevant internships during the holidays, and more male students tend to select into science subjects than female students (Quadlin 2020).[4] Second is a set of covariates which I call 'propensity to work' characteristics at compulsory schooling age. If students with specific characteristics are more likely to work at a younger age, they are also more likely to also work during university. These controls are socio-economic and attitudinal variables up until age 15/16 which may determine the students' engagement in early work. These are whether the household is managing quite well with their income, whether they have ever received an Education Maintenance Allowance (EMA) which is a means-tested allowance for students aged 16 - 19 to encourage students to stay in education, attitudes towards school (a sum score from 12 attitudinal questions relating to how the student felt about school), and whether the students' house is owned/on mortgage/shared ownership.

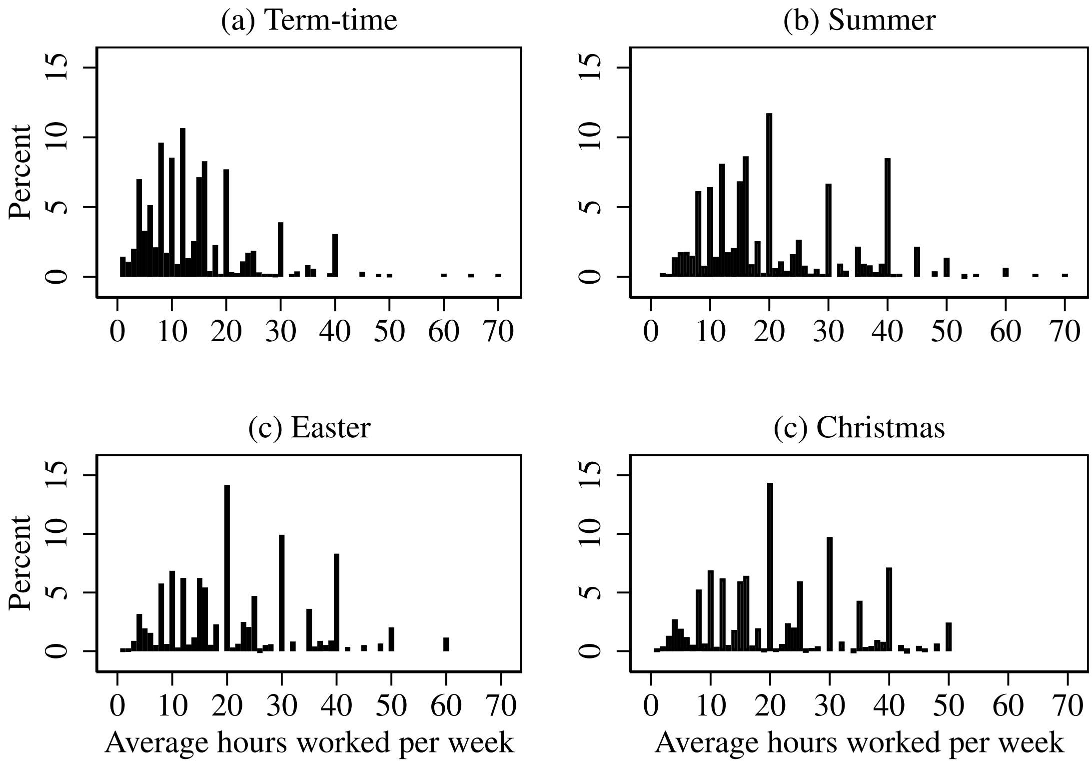
[4] Appendix Table A3.2 show that there are no striking differences in work engagement by university subject, except for subjects with few students (e.g., n=19 for veterinary science). Therefore, I use a binary variable equal to 1 if the student is in a science subject, and 0 otherwise. Appendix Figure A3.4 show that more female students are in non-science subjects, and more likely to engage in work.

3.5 Characteristics of university students

3.5.1 Students' engagement in work

For students who worked, Figure 3.2 reports the distributions of average working hours per week for students who worked during (a) term-time (b) Summer (c) Easter and (d) Christmas. During term-time, 85% of the working students worked 20 hours or less a week, namely 8, 12 and 16 hours a week. This corroborates with the ONS (2021) that the average hours worked by part-time UK workers aged 16 and above was 15.7 hours a week in 2010.

Figure 3.2: Histogram of average weekly hours worked, by period



During the holidays, the modal hours reported were 20, 30 and 40 hours a week, suggesting that students either engaged in full-time work or took on more shifts. However, these are likely still part-time jobs as about two thirds of the students still worked 20 hours a week or less. There is currently no standard recommended maximum hours of work for students. Most universities in the UK recommend that students do not work for more than 15 hours a week, and this level is capped at 20 hours a week for students with visas. To assess whether these thresholds are "critical" to skills development, I examine whether working more than 15 or 20 hours of work per week is detrimental to students' skills accumulation.

Since I do not observe the types of paid work students do in the NS data, I provide a descriptive proxy in Appendix Table A3.3 using data from the Annual Population Survey (APS) (ONS 2017). Students' average characteristics in the APS mirror those in the NS data; about a third of students were in paid employment, with more female students being in employment than male students, and the majority were sampled in England.

For those who were in paid employment, the majority were in part-time employment. A third of students worked in elementary occupations, a third in sales and customer service occupations, and the rest in other occupations. Nearly 70% worked in the distribution, hotels and restaurants industries. Therefore, we can expect that the majority of students were working as bar staff or cashiers. Male students were more likely to be in skilled trades and elementary occupations whereas females were more likely to be in personal service, and sales and customer service occupations, which may be more customer-facing. There were few differences in the types of work students did during term time and during the holidays, barring occupations such as transport and communication and professional occupations.

3.5.2 Student background differences

Appendix Table A3.2 shows the average background characteristics of students who never worked in university in column (a), have ever worked (at least once in each of the periods) in column (b), and the t-test of differences between the groups (a)-(b). Students who have ever worked have slightly higher LOC than students who do not work. They also are more likely to be female and white. Students who have worked are also more likely to be in their second year of undergraduate, and are less likely to attend a Russell Group University. Notably, students who work are also more likely to be taking a non-science subject.

In terms of family background, students who work do not seem more or less advantaged than their non-working peers. However, this is masked by the period in which students work. In Table 3.1, students who work during term-time and Summer are more likely to receive financial help for university, less likely to have a parent with higher education, and more likely to have received an EMA at age 15/16. These gaps are less evident during Christmas and Easter, as seen in Table 3.2. Therefore, it is likely that less advantaged students are working during term-time and Summer, which is work that competes with social activities at university and academic obligations.

Students' attitudes towards school were similar across all working and non-working groups. This provides some reassurance at least, that students doing paid work in my sample are not less academically motivated, nor are they making decisions about university to keep their job compared to non-working students, as argued to be important selection issues in primary orientation theory.

Table 3.1: Average characteristics of students background by work status: Term-time and Summer

	Term-time			Summer		
	Not Worked	worked	Diff	Not Worked	worked	Diff
	(a)	(b)	(a)-(b)	(c)	(d)	(c)-(d)
Locus of control, wave 7	11.18	11.39	-0.15*	11.21	11.35	-0.12
Standardised locus of control, wave 7	0.00	0.10	-0.08	0.01	0.09	-0.09*
Locus of control, wave 2	12.10	12.16	-0.02	12.09	12.18	-0.08
Standardised locus of control, wave 2	-0.03	-0.02	0.01	-0.04	0.01	-0.05
Ever worked during term-time	0.00	1.00	-1.00	0	1	-1
Avg weekly hours worked during term-time	0.00	14.46	-14.17***	0	20.8	-19.49***
Student characteristics						
Sex: Male	0.50	0.41	0.10***	0.48	0.44	0.04*
Ethnicity: White	0.82	0.84	-0.04	0.83	0.83	0.02
Health problem or disability at Wave 7	0.09	0.06	0.02	0.09	0.06	0.02*
Receives a financial help with university costs	0.55	0.63	-0.07***	0.56	0.61	-0.05*
Enrolled in wave 6	0.66	0.79	-0.11***	0.69	0.73	-0.04*
Science subject	0.42	0.32	0.08***	0.42	0.3	0.12***
Attending a Russell Group University	0.32	0.22	0.10***	0.34	0.18	0.15***
Family background						
Main parent has higher education	0.49	0.39	0.07***	0.49	0.37	0.10***
Lone parent/no parent family	0.14	0.17	-0.03	0.14	0.17	-0.03
Number of siblings	1.62	1.57	0.09	1.6	1.6	-0.04
Propensity to work, age 15/16						
Household managing quite well with income	0.68	0.62	0.04	0.67	0.63	0.02
Ever received EMA	0.32	0.36	-0.02	0.32	0.38	-0.06**
Attitude towards school, age 15/16	35.67	35.43	0.31	35.82	35.06	0.63*
House is owned/on mortgage/shared ownership	0.88	0.88	-0.01	0.88	0.87	0.03
Observations	1572	854	2426	1687	739	2426

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values are for the t-test to examine differences between groups (a) and (b) and (c) and (d). All information are obtained from wave 7 when the young person was aged 20/21 unless otherwise stated. Observations shown is raw sample size, but estimates are obtained using wave 7 population probability weights and accounting for clustering at the school level. Financial help refers to receiving a grant, bursary, or scholarship to help with university costs. Attitudes towards school is derived sum score of 12 questions about the students' attitude towards school, ranging from 0 to 48. The higher the score, the more positive the attitude towards school.

Table 3.2: Average characteristics of students background by work status: Christmas and Easter

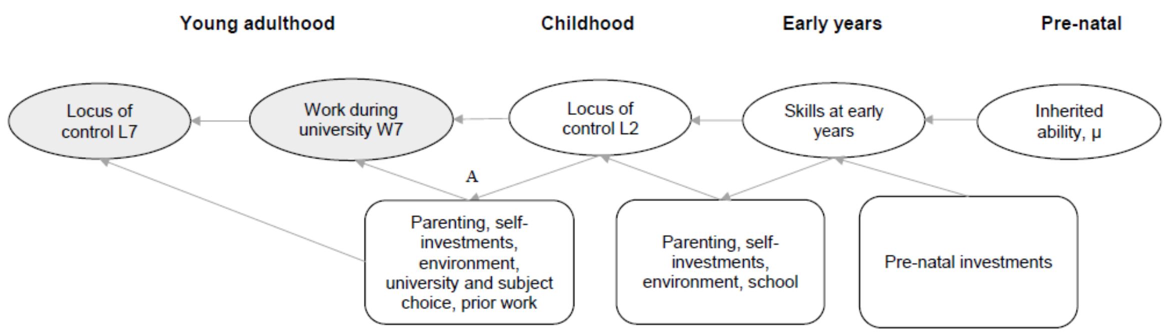
	Christmas			Easter		
	Not Worked	worked	Diff	Not Worked	worked	Diff
	(a)	(b)	(a)-(b)	(c)	(d)	(c)-(d)
Locus of control, wave 7	11.19	11.32	-0.15*	11.22	11.27	-0.02
Standardised locus of control, wave 7	0.00	0.04	-0.06	0.02	0.01	0.00
Locus of control, wave 2	12.08	12.18	-0.11	12.08	12.18	-0.07
Standardised locus of control, wave 2	-0.03	-0.01	-0.03	-0.03	-0.02	0.00
Student characteristics						
Sex: Male	0.51	0.43	0.08***	0.51	0.44	0.05*
Ethnicity: White	0.80	0.85	-0.09***	0.80	0.86	-0.11***
Health problem or disability at Wave 7	0.09	0.06	0.02*	0.09	0.06	0.02*
Receives a financial help with university costs	0.56	0.61	-0.03	0.58	0.58	0.00
Enrolled in wave 6	0.67	0.73	-0.05*	0.67	0.73	-0.05*
Science subject	0.41	0.35	0.07***	0.41	0.34	0.06**
Attending a Russell Group University	0.33	0.22	0.11***	0.32	0.23	0.09***
Family background						
Main parent has higher education	0.50	0.38	0.07***	0.49	0.39	0.05*
Lone parent/no parent family	0.15	0.15	0.00	0.15	0.13	0.02
Number of siblings	1.63	1.58	0.10	1.64	1.56	0.15**
Propensity to work, age 15/16						
Household managing quite well with income	0.65	0.68	-0.04*	0.65	0.68	-0.06**
Ever received EMA	0.34	0.33	0.03	0.35	0.31	0.06*
Attitude towards school	35.46	35.70	-0.25	35.60	35.46	0.29
House is owned/on mortgage/shared ownership	0.87	0.89	-0.04*	0.87	0.90	-0.04**
Observations	1385	845	2230	1479	751	2230

See notes for Table 3.1 above.

3.6 Empirical strategy

I follow models widely used in measuring the production of socio-emotional skills for children (e.g., Cunha and Heckman (2008) and Todd and Wolpin (2007)), but allow the student, as a young adult, to also make his/her own inputs (such as models by Elkins and Schurer (2018) and Kassenboehmer, Leung, and Schurer (2018)). The model estimates the production of each student's LOC at wave 7 as a function of inputs made by the student and their family throughout the student's life cycle up until that period. Figure 3.3 summarises a simple framework regarding how students' LOC observed in wave 7 is determined by investments and stocks of skills throughout their life cycle, simplified as four stages of life: pre-natal, post-natal, childhood and young adulthood. Each individual is born with inherited traits, μ, and thereafter, his/her skills are jointly determined by inputs (squares at the bottom) as well as his/her prior stocks of skills (circles in the middle). μ is termed inherited ability, but can be thought of as many facets of ability such as cognitive, physical and mental ability.

Figure 3.3: Illustrative framework of skills development



Note: The two shaded circles indicate the variables of interest in this analysis. Adapted from Heckman, Jagelka, and Kautz (2021)

I am interested in the effect of work during university on students' LOC at wave 7 (the two shaded circles to the left). Isolating the effect of work on students' LOC is difficult as I am faced with two endogeneity problems: unobservable heterogeneity and simultaneity.

Unobserved heterogeneity is the unobservable differences between students who work and do not work, such as their inherited ability, μ, or other relevant unobservable characteristics (e.g., skills at early years) that are not captured in the data that may affect both students' work and LOC. Depending on the correlation between the unobservable characteristics and work hours, my estimate regarding the association of working hours on students' LOC may be upward or downward biased. For example, if students with a strong work ethic select more work hours and have a greater internal LOC, then my estimate will be upward biased. To minimise these problems, I employ a value-added (VA) model, which I elaborate more below. The VA model uses lagged observed LOC, L2, to capture unobserved heterogeneity, and prior investments and life choices (i.e., pre-natal to childhood inputs) made by students and/or their families up until wave 2 (see Section 1.7 in Chapter 1 for an in-depth discussion about VA models).

However, only observing lagged LOC at age 15/16 in wave 2 leaves a large unaccounted window of inputs until age 20/21. Important decisions made in this window may simultaneously have determined both students' LOC and their decision to work during university in wave 7. I specify two major concerns. First, students with higher (or lower) internal LOC in wave 2 may have chosen a university or subject that may have determined their LOC in wave 7, as well as their ability to engage in work during university; this can be visualised by the indirect arrow from L2 to L7, indicated by A. If students with more internal LOC select into more prestigious universities (which may have strict rules about work hours, such as Oxford or Cambridge) or select into subjects that have greater restrictions on work (e.g., Medicine compared to History), more internal students may not select into work at university. Second, students with a high (or low) internal LOC at wave 2 who may have had a higher or lower propensity to work before university, which consequently impacted on their decision to work during university.

To account for these inputs, I first include a control for university subjects. I then include the 'propensity to work' variables, as previously described, characteristics which are expected to be key determinants of students' engagement in employment before university, up until age 14/15.

Using VA models, I use step-wise regressions as follows. For each student in university at wave 7 (age 20/21), I estimate the following:

$$L_7 = \beta_0 + \beta_1 W_7 + \beta_2 X_7 + \beta_3 B_2 + v_7 \tag{3.1}$$

$$L_7 = \beta_0 + \beta_1 W_7 + \beta_2 X_7 + \beta_3 B_2 + \beta_4 L_2 + e_7 \tag{3.2}$$

$$L_7 = \beta_0 + \beta_1 W_7 + \beta_2 X_7 + \beta_3 B_2 + \beta_4 L_2 + \beta_5 P_4 + \varepsilon_7 \tag{3.3}$$

$$L_7 = \beta_0 + \beta_1 W_7 + \beta_2 X_7 + \beta_3 B_2 + \beta_4 L_2 + \beta_5 P_4 + \beta_6 U_7 + \varepsilon_7 \tag{3.4}$$

where my main coefficient of interest is β_1, the effect of university students' paid work, W_7, on their LOC, L_7. I estimate the associations of work on LOC in four periods; term-time, Summer, Christmas and Easter. The reference group is university students who did not work during term-time i.e., those who performed zero hours of work. X_7 is a set of student-specific controls, B_2 is a set of family background characteristics up to age 15/16 (wave 2).

Model (3.2) include L_2, the LOC at age 15/16, and model (3.3) adds P_4, the propensity to work characteristics and model (3.4) adds U_7, whether or not the student took a science subject. By consecutively adding covariates and checking whether β_1 changes, I am using a coefficient comparison test to examine whether paid work is as good as random after the selection on observables (Pei, Pischke, and Schwandt 2019). This is confirmed if the estimated effect of interest (work on LOC) is insensitive to this variable addition. In addition, I also conduct a balancing test where the variable is placed on the left-hand side (LHS) of the regression instead of the outcome variable. A zero coefficient on work will confirm the identifying assumption (Pei, Pischke, and Schwandt 2019).

All of my estimates are weighted using wave 7 weights. I re-run these estimates using hours of work to examine whether the relationships between paid work and locus of control change at very low or high hours of paid work. I also re-run the estimates by students' sex, as female students compared to male students may have different preferences towards work and study, as discussed before in sub-section 3.3.3.

The models makes several assumptions. All of the control variables and lagged LOC are a good proxy of any unobserved inputs and unobservable characteristics of the student. Second, the effects of the inputs are assumed to decline with the number of years since the application of the input, and the rate of decline is the same for each input, at the rate of β_2. That is, the effect of working at age 14 is assumed to have a greater impact on LOC at age 17 than at age 20, and these effects decline at a constant rate. Third, the error terms are assumed to be serially correlated, with the degree of serial correlation matching the rate of decline of the input effects. Finally, the model assumes that there is no remaining unobserved heterogeneity that correlates with the decision to work at age 20/21.

Clearly, the model relies on strict assumptions, and there may be good reasons why the assumptions will be violated. The model does not completely alleviate the simultaneity problem, as engagement in paid work at age 20/21 may also be correlated to previous values of LOC. To minimise this concern, I run a probit estimation as a sensitivity analysis to examine whether previous LOC is associated with students' engagement in work, and I find little evidence for this (see Appendix Table A3.16). Regardless, I interpret my findings as associations between work and LOC, while accounting for as much selection on observables, and using lagged LOC as a proxy for unobservables under strict assumptions.

3.7 Estimates

3.7.1 University employment and locus of control

My coefficient estimates of university students' work on their LOC are presented in Tables 3.3 and 3.4. I examine these relationships by whether the student had ever worked, worked during term-time, Summer, Christmas, and Easter. Columns (1) to (34) correspond to models 3.1 to 3.4 above.

Looking at the full estimates in Appendix Tables A3.4 to A3.8, consecutively adding the lagged LOC, and propensity to work characteristics reduces the coefficient magnitude of work on LOC slightly. This suggests that students with higher early internal LOC select into paid work during university. However, in column (4), controlling for science subject raises the coefficient magnitude slightly, suggesting an opposite selection. As discussed above, an alternative test to adding controls on the right hand side of the equation is a balancing test which instead places the controls on the left hand side of the equation (Pei, Pischke, and Schwandt 2019) (see Appendix Table A.3 for a more comprehensive test). In Appendix Table A3.11, I run balancing tests for those who "ever worked" and find that all controls are suitable except for the science subject indicator. The statistically significant estimate in column 2 of Appendix Table A3.11 indicates that students who engage in paid work are less likely to study science subjects. While the science subject indicator may be conceptually important, I find that it is a poor control as per the balancing test. Therefore, my preferred final model in Tables 3.3 and 3.4 are between columns (1) and (3), reported in the main estimates. Notably however, there are few statistically significant associations between 'propensity to work' characteristics except for attitude towards school and whether the family owns their home, thus these characteristics are also unlikely to do much in absorbing the unobserved differences between individuals who are likely to work or not. This suggests that the lagged LOC does the most to account for these unobserved variables.

Table 3.3 shows that students who engaged in paid work were associated with greater internal LOC, but only statistically significant for ever worked and term-time work, not for work during Summer. This suggests that students stand to gain some form of socio-emotional skills through paid work experience during university. Students who did some form of paid work had 0.08 standard deviations, and students who worked term time are associated with 0.11 standard deviations more internal LOC, compared to students who did not work. The coefficient size is comparable to a handful of other statistically significant covariates, such as being male (0.15 standard deviations) or white (0.07 standard deviations). Comparing my findings with Callender (2008), who found that term-time work reduces students' academic achievement, may suggest that work promotes different skills sets to studies. It may also be that work lowers students' cognitive skills by competing with time for academic commitments, but not for activities important for their socio-emotional competencies.

During the holidays in Table 3.4, students who worked over Christmas are associated with 0.04 standard deviations more internal LOC while estimates for students who worked over Easter are close to zero, but both sets of estimates are statistically insignificant.

In sum, students engaged in paid work are associated with greater internal LOC, and this association is strongest and statistically significant for having ever worked and term-time work, but not work during the holidays. This provides evidence for the human capital theory that work helps skills, also as shown by Gottshalk (2005) that work can enhance LOC. One possible explanation why it may only be term-time paid work that is statistically significant is that the ability to do both paid work and studies is an important set of skills associated with LOC. Another possible explanation is that students may be engaged in more "useful" types of paid work during term-time than in the holidays – especially if the work is more related to their studied subject.

Table 3.3: Coefficient estimates of work on locus of control: ever worked, term-time, and Summer

	Ever worked			Term-time			Summer		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Engaged in work	0.084*	0.074*	0.077*	0.100**	0.100**	0.105**	0.078	0.062	0.070
	(0.047)	(0.044)	(0.044)	(0.047)	(0.045)	(0.045)	(0.049)	(0.047)	(0.047)
LOC age 15/16	-	0.295***	0.290***	-	0.296***	0.279***	-	0.295***	0.278***
		(0.023)	(0.023)		(0.024)	(0.024)		(0.024)	(0.024)
Propensity to work	X	X	V	X	X	V	X	X	V
Observations	2426	2426	2426	2426	2426	2426	2426	2426	2426

* $p < 0.05$, ** $p < 0.05$, *** $p < 0.001$. Standard errors are reported in parentheses. All information is obtained from wave 7 when the young person was aged 20/21 unless otherwise stated. Observations shown is raw sample size, but estimates are obtained using wave 7 population probability weights and accounting for clustering at the school level. All student-specific and family background characteristics are included as specified in Table 3.1. X indicates that the set of controls are excluded, and V indicates that the set of controls are included.

Table 3.4: Coefficient estimates of work on locus of control during Christmas and Easter

	Christmas			Easter		
	(1)	(2)	(3)	(1)	(2)	(3)
Engaged in work	0.047	0.038	0.043	-0.002	-0.009	-0.003
	(0.051)	(0.046)	(0.045)	(0.048)	(0.046)	(0.046)
LOC age 15/16	-	0.299***	0.283***	-	0.299***	0.283***
		(0.024)	(0.025)		(0.024)	(0.025)
Propensity to work	X	X	V	X	X	V
Observations	2230	2230	2230	2230	2230	2230

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. See Table 3.3 above.

3.7.2 Average hours of work and locus of control

I then examine whether the LOC associations change with increasing average hours worked per week, only for students who were employed in the respective periods. I only use the sample of students who were engaged in paid work, as these are my intensive margins of interest. Given the positive association between paid work and LOC, I examine whether this more-is-better relationship holds at higher hours of work. Table 3.5 reports the coefficient estimates using i) a continuous measure of hours worked a week, ii) including a squared-term to examine if the relationship is non-linear and iii) using a categorical variable which includes cut-offs of 15 and 20 hours a week, where the counterfactual category is 1-8 hours of work a week. Cut-offs of 15 and 20 hours a week are used because they are commonly cited in the literature as the "excessive hours" of work, and is the recommended cut-off hours of work for migrant students in the UK. In this section, I only describe the variation in average work hours for students in paid work as these are my intensive margins of interest.

I do not find a significant variation in LOC with average hours worked per week. Panel A of Table 3.5 shows that an additional hour of work hardly changes students' internal LOC and is statistically insignificant or the estimate is close to zero. I do not find non-linearities with increasing hours of paid work, as shown by the zero coefficient estimates on the squared terms in panel B. In Panel C, working 20 hours a week or more in term-time paid work compared to 1-8 hours a week is positively associated with students' internal LOC. However, this is only relevant for term-time paid work and not in the other periods. It may be that specific work taken up during term-time that requires intensive weekly hours provides greater internality to students. However, I also cannot rule out that students who have very high LOC are taking on more hours of work. Overall, the only important difference in LOC is linked to those who worked and those who did not work, not the hours of work.

Table 3.5: Coefficient estimates of average weekly work hours on locus of control in wave 7, for employed students

	Term-time	Summer	Christmas	Easter
(A) Continuous measure of hours worked a week				
Average weekly hours worked	0.008**	0.003	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
(B) Squared hours worked a week				
Average weekly hours worked	0.012	0.006	0.007	0.001
	(0.009)	(0.010)	(0.011)	(0.011)
Squared terms for average work hours	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
(C) Using cut-off points (1-8 hours a week as the baseline)				
9-15 hours a week	0.065	0.099	0.014	0.009
	(0.081)	(0.125)	(0.114)	(0.114)
16-20 hours a week	0.146	0.131	0.088	-0.037
	(0.107)	(0.132)	(0.122)	(0.108)
>20 hours a week	0.294***	0.158	0.131	0.082
	(0.101)	(0.120)	(0.101)	(0.100)
p-values test for difference in coefficient estimates				
1-8 hours = 9-15 hours	0.428	0.431	0.903	0.938
9 -15 hours = 16-20 hours	0.437	0.787	0.517	0.666
16-20 hours = >20 hours	0.222	0.806	0.662	0.217
1-8 hours = >20 hours	0.174	0.321	0.472	0.733
Joint significance	0.030	0.622	0.498	0.631
Observations	842	739	845	751

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors reported in parentheses. Sample only consists of those who worked in the respective period during university (i.e., does not include zero hours of work). All student characteristics, family background, lagged LOC, propensity to work characteristics are controlled for, as specified in column (3) of Table 3.3.

3.7.3 Differences by sex

In previous sections, I described how female and male students may have different preferences for subject choice (which determine their ability to work) and different preferences for types of work. Table 3.6 demonstrates the baseline estimates of doing paid work, interacted by the students' sex.

Again, the only estimate that is statistically significant is for term-time paid work for females. All estimates for non-working males are positive and significant, showing that being male is associated with greater LOC. All interaction terms however, are negative, which indicate that males in work have lower LOC compared to females in work, but these differences are not statistically significant. I then re-run estimates by hours of work as seen in Appendix Figure A3.6 and while there is a small divergence by hours of term-time work, and a convergence with work during the holidays, there are no overall sex differences by hours of work. Therefore, my findings are in contrast to my hypothesis that there may be gendered differences in the associations between paid work and LOC due to gendered preferences.

Table 3.6: Paid work estimates on locus of control, by sex

	Ever worked	Term-time	Summer	Christmas	Easter
Engaged in work	0.106	0.141**	0.020	0.041	-0.030
	(0.067)	(0.059)	(0.067)	(0.065)	(0.065)
Male	0.188**	0.182***	0.116**	0.169***	0.147**
	(0.074)	(0.058)	(0.056)	(0.061)	(0.058)
Engaged in work x Male	-0.057	-0.080	0.108	-0.006	0.059
	(0.088)	(0.088)	(0.094)	(0.089)	(0.088)
Observations	2426	2426	2426	2230	2230

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors reported in parentheses. All student characteristics, family background, lagged LOC, university subject, and prior characteristics are controlled for, as specified in Table 3.3.

3.7.4 Sensitivity checks

I run several sensitivity checks to ease concerns about sample size differences, how the LOC score is measured, and analyse the potential degree reverse causation between LOC and engagement in work. To ease concerns about sample differences because of the questionnaire re-routing, Appendix TableA3.12 re-estimates my baseline estimates using the most constrained sample i.e., the sample which excludes students who were in term-time and had a job. My estimate for term-time work remains positive but becomes statistically insignificant, arguably from a lower power, with a slightly lower magnitude of 0.07 standard deviations. The estimate for paid work in Summer nearly doubles to 0.09 standard deviations, significant at the 5% level, from overestimating the number of students in Summer work through sample constraints. Regardless, constraining the sample does not change the overall interpretation of my estimates that there is a positive relationship between work and LOC.

Regarding how LOC is measured, Appendix Table A3.13 shows estimates if responses of "Don't know" to LOC items were instead coded as a "middle" score instead of being dropped (i.e., coded as 3 in a scale of 1—5). The sample size inflates, as well as the statistical significance of the estimates for ever worked and Summer work, but sizes of the coefficients remain similar, especially for term-time work. Appendix Table A3.14 uses sum scores of LOC instead of factor analysis, and shows that my estimates also remain similar but are arguably more difficult to interpret. Hence, my baseline estimates are the most prudent lower bound estimate in comparison. Lastly, by wave 7, the sample had fallen to 8,682, and I am using a select sample of university students of 3,543. Using casewise deletion from 3,543 to 2,043 raises the concern around missingness. In Appendix Table A3.15 I re-ran my estimates using 20 multiple imputations to account for the missing information (assuming "Don't know" is missing), and estimates are similar, except that coefficient estimates are slightly inflated, and have more statistical power.

Finally, there may be concerns that students' LOC is instead a predictive factor of their engagement in work, meaning that my baseline estimates may be estimating both the effect of paid work on LOC, and vice versa. Appendix Table A3.16 reports the predicted probability of students' LOC at age 14/15 on students' engagement in term-time work at age 20/21. I do not find evidence that students' prior LOC predicted their likelihood of engaging in term-time work, and the marginal effects for paid work are small and statistically insignificant, except for Summer work but this is less of a concern since my main findings are for term-time work. Instead, the predictors strongly associated with an increased probability of working are variables such as being of white ethnic background, enrolled in Wave 6, attending a Russell Group University, main parent has higher education, all which were controlled for in my baseline estimates to absorb observed student differences.

3.8 Summary and conclusion

I examined whether English university students doing paid work helps students to develop socio-emotional skills, measured by internal LOC. Students may find themselves better equipped to have control over their lives through their paid work experience, or instead, find that time in work competes with time for studies and leisure, reducing their LOC. There may also be a small or null association between paid work and LOC if students can balance their time wisely between work, leisure, and education.

First, I analysed whether doing paid work during term-time or the holidays, or having worked in any of these periods, is associated with improved LOC. I find that students who have ever worked and worked during term-time have greater internal LOC compared to students who do not work. This finding is in line with Baert et al. (2022) who found that students who work both during term-time and Summer gain the most returns in terms of employability. The estimates for term-time work are statistically significant, but not for the holidays, which suggest that the types of work done during the academic term may be helpful for socio-emotional skills development. For instance, it may be that jobs available during term-time may be more relevant to the students' subject or the types of jobs chosen are ones which interfere less with other competing demands, compared to greater flexibility during the holidays. Overall, my findings provide support for the human capital theory that work helps students gain skills not captured by academic achievement, and there is little evidence for zero sum theory that work crowds out time for activities important for socio-emotional skills.

Second, I examined how this relationship changed with increasing hours of work. While engagement in work is associated with greater internality, I do not find any added marginal associations to LOC with more hours of work. This finding is similar to Callender (2008) who finds that it is the engagement in work that is associated with lower students' academic achievement, but not the hours of work. This may be due to students practicing good time management strategies during paid work, that higher hours of work do not deter skills development, as posited by the reconciliation approach.

Lastly, I examine differences in these relationships by gender, as male and female students may have different preferences for types of work, and types of subjects which determine their availability for paid work. I find little differences by gender, whether it is by engagement or hours of work. In summary, my study shows that students can gain socio-emotional skills from work, contributing to research which find that adolescent employment can bring about non-academic benefits (Cunnien, Rogers, and Mortimer 2009; Painter II 2010; Lesner et al. 2018), and that work is positively associated with enhanced LOC (Gottshalk 2005).

My study is not without limitations; I do not observe types of work, nor can I fully disentangle whether work improves students' skills, or vice versa. The NS data only examines a cohort of students from 1990/91, who may have made different decisions about their university, subject choice and decision to work during university because of the Great Recession that occurred in 2008. Since this is a cohort study, and I use a selected sample, these findings are not generalisable to other populations. The missing information in the study due to attrition also likely biases my estimates for adolescents who are more motivated, and stay in the longitudinal sample. The main strengths of this study are placing focus on socio-emotional skills as an outcome of interest, and in using longitudinal data which allows me to control for a rich set of individual background characteristics in my analysis.

These empirical findings may have a wider relevance for policy makers and future researchers. While I find that students' involvement in paid work can bring some form of benefits in terms of socio-emotional skills, it is unclear if this comes at a cost to academic achievement as found by previous UK research (Callender 2008). Given that student employment has the potential to widen or narrow inequalities in student outcomes, more research is needed to examine the full cost and benefits to student employment. Future studies should examine both the cognitive and socio-emotional implications from student employment, and investigate other non-academic outcomes such as self-esteem, involvement in university social activities, and mental wellbeing. Future research should also examine these relationships by type of employment and the relevance of work to their subject of study, as studies show that subject relevance can help improve outcomes (Passaretta and Triventi 2015; Geel and Backes-Gellner 2012).

Higher education institutions should review the evidence about the costs and gains to paid work in order to provide suitable employment advice to students. To do so, data about university students' work engagement needs to be available, which in the UK, is currently difficult to come by. A suggested UK policy recommendation is for the HESA to collect and publish information on students' work engagement during their studies, and the types of work they do. More data could help encapsulate a more holistic version of the student experience, which may assist in consolidating the recommended hours of student work across UK universities.

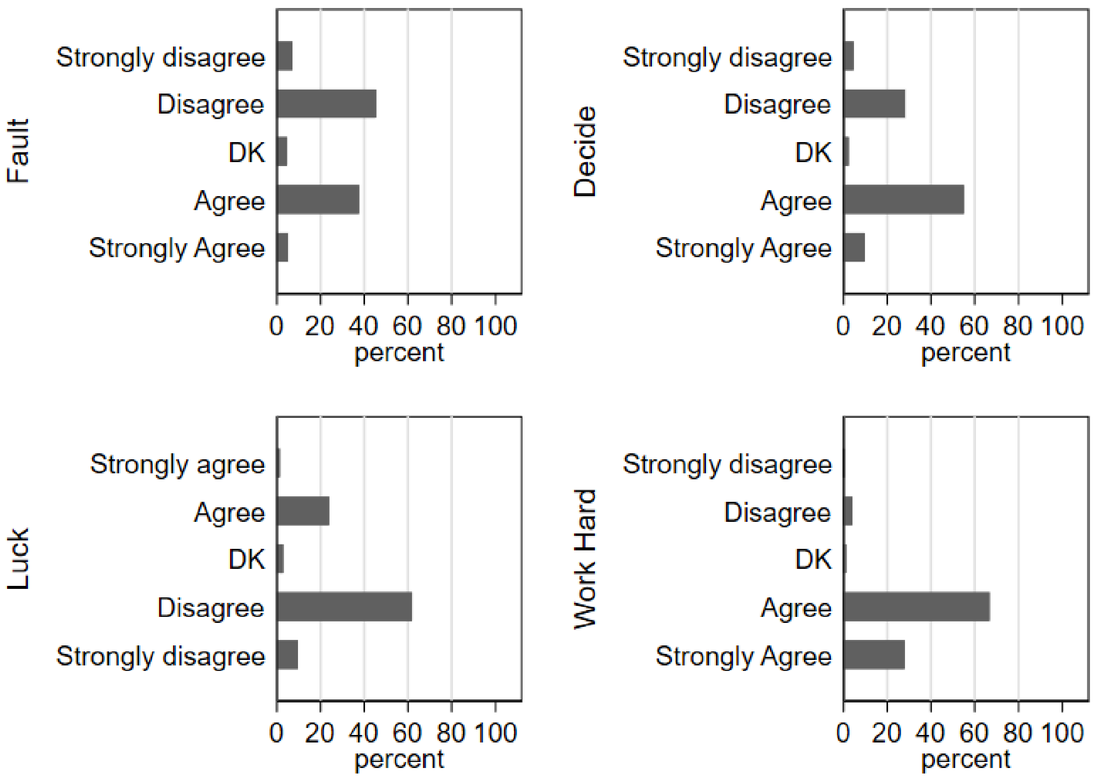
3.9 Appendix A

3.9.1 Background information and descriptive statistics

Table A3.1: Factor loadings of LOC in waves 2 and 7

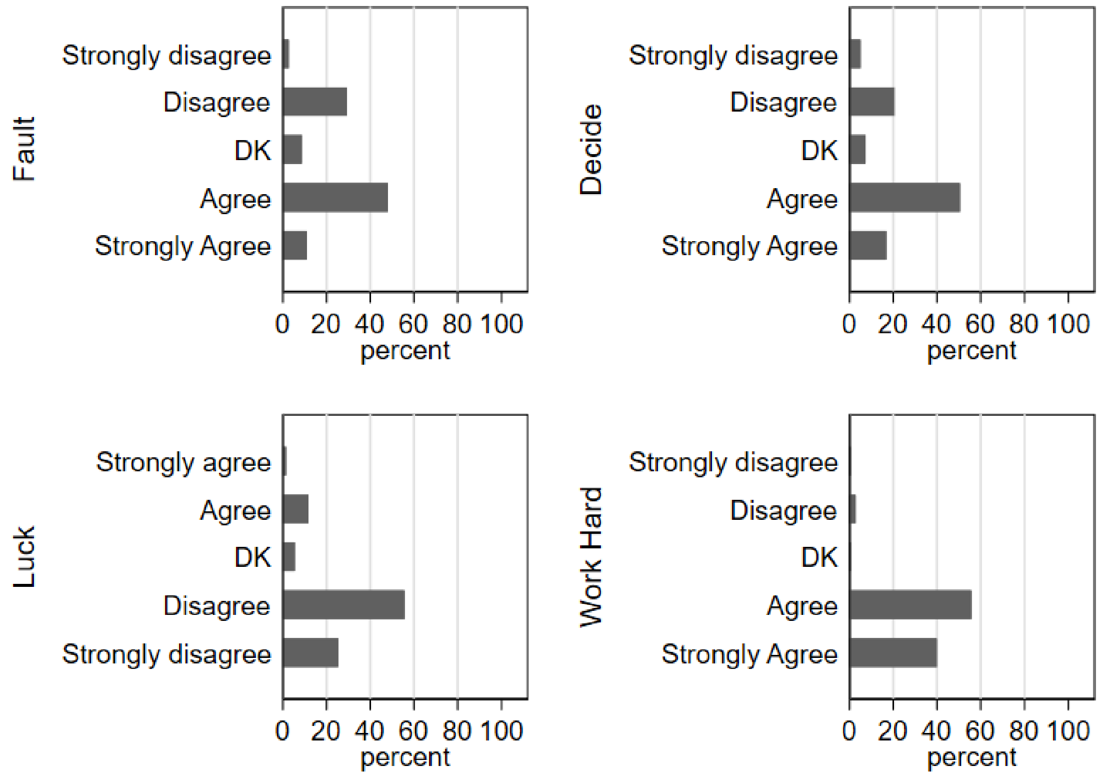
Items	Wave 7	Wave 2
If someone is not a success in life, it is usually their own fault	0.443	0.291
I can pretty much decide what will happen in my life	0.484	0.331
If you work hard at something, you'll usually succeed	0.394	0.377
How well you get on in this world is mostly a matter of luck	0.182	0.161

Figure A3.1: Categorical plots of responses to Locus of Control items in wave 7



Note: The LOC items are plotted using wave 7 weights. Items for Fault, Decide and Work Hard are reverse coded and responses for "Don't Know" and "Refused to Answer" are dropped.

Figure A3.2: Categorical plots of responses to Locus of Control items in wave 2



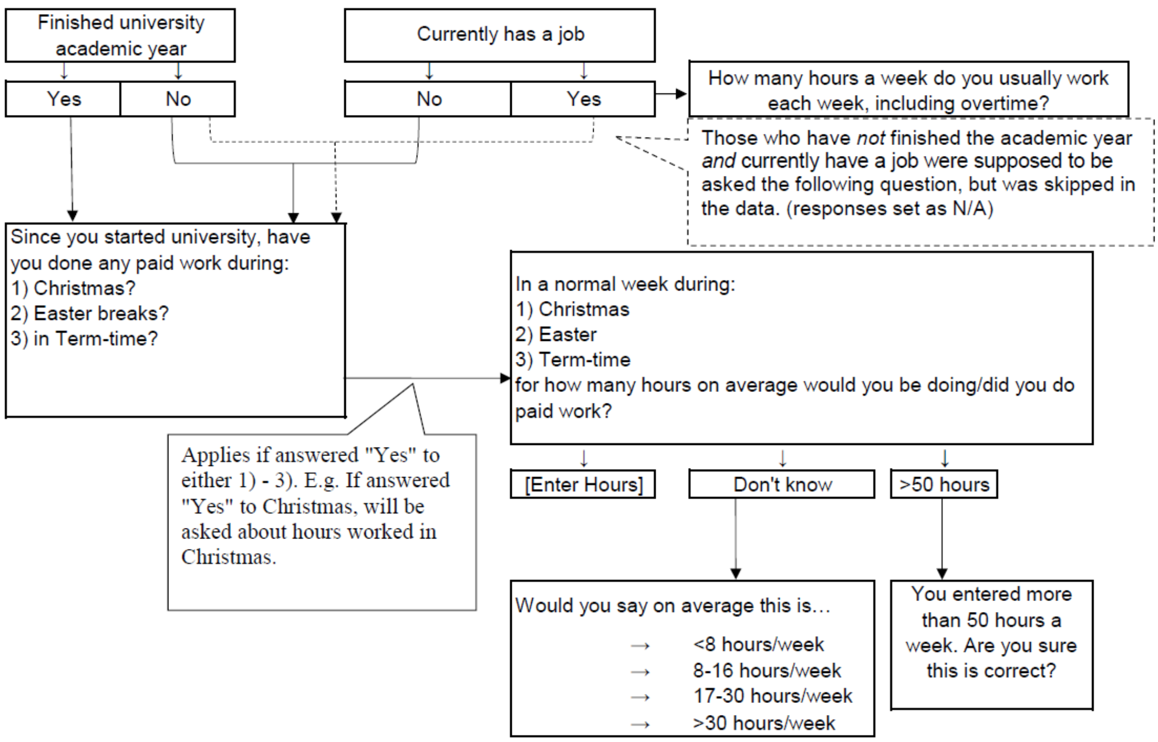
3.9.2 How involvement in paid work is measured for university students in Next Steps data

The questionnaire was structured in two ways to capture student work. The first way was through a retrospective question "Since you started university, have you done any paid work during term-time/ Christmas/ Easter?". All students who had finished their academic term, or students without a current job who had not finished their academic term were asked this question. Conditional on whether or not they had worked, their average weekly hours were derived from the question "In a normal week during term time/ Christmas/ Easter for how many hours on average did you do paid work?".

The second way was through, let's call it, a "current" question. Regardless of whether or not they had finished their academic term, students also reported whether they currently had a job at the time of the interview and the hours they usually worked in the job each week, including overtime. The question routing error missed students who currently had a job but had not finished their academic term. In other words, students who were working during term-time at the time of interview are missing their employment history about the previous Christmas or Easter.

Acknowledging this routing problem, I measure four periods in which students do paid work; term-time, Summer, Easter and Christmas. I define term-time work as students who answered "yes" to the retrospective question for term-time work, and those who currently had a job and had not yet finished their academic term. Work during Summer holidays is measured as students who currently had a job and had finished their academic term. I use the term "Summer" because two thirds of students who had finished their academic term were interviewed between May and July. Finally, work at Christmas and Easter only refers to students who answered the retrospective question, who constituted 92% of the full sample.

Figure A3.3: Question routing of work during university in the Next Steps data



Note: Information is processed according to author's discretion, following question routing in the Next Steps questionnaire (University College London 2021)

Table A3.2: Percentage of students who worked by period

Period worked	(%)
Sample for Summer and term-time	
Did not ever work	54
Only during term-time	20
Only during Summer	11
Both during term-time and Summer	15
Percentage in any forms of work	
Any term-time work*	36
Any Summer work*	31
Observations	2,043
Sample for retrospective work responses	
Did not ever work	44
Only during term-time	3
Only in holidays	26
Both during term-time and holidays	27
Percentage in any forms of work	
Any term-time work	30
Only during term-time	5
Both during term-time and holidays	25
Any Summer work	33
Only in Summer	11
Both Summer and term-time	22
Any Christmas work*	39
Only in Christmas	17
Both Christmas and in term-time	22
Any Easter work*	35
Only in Easter	22
Both Easter and in term-time	13
Observations	1,877

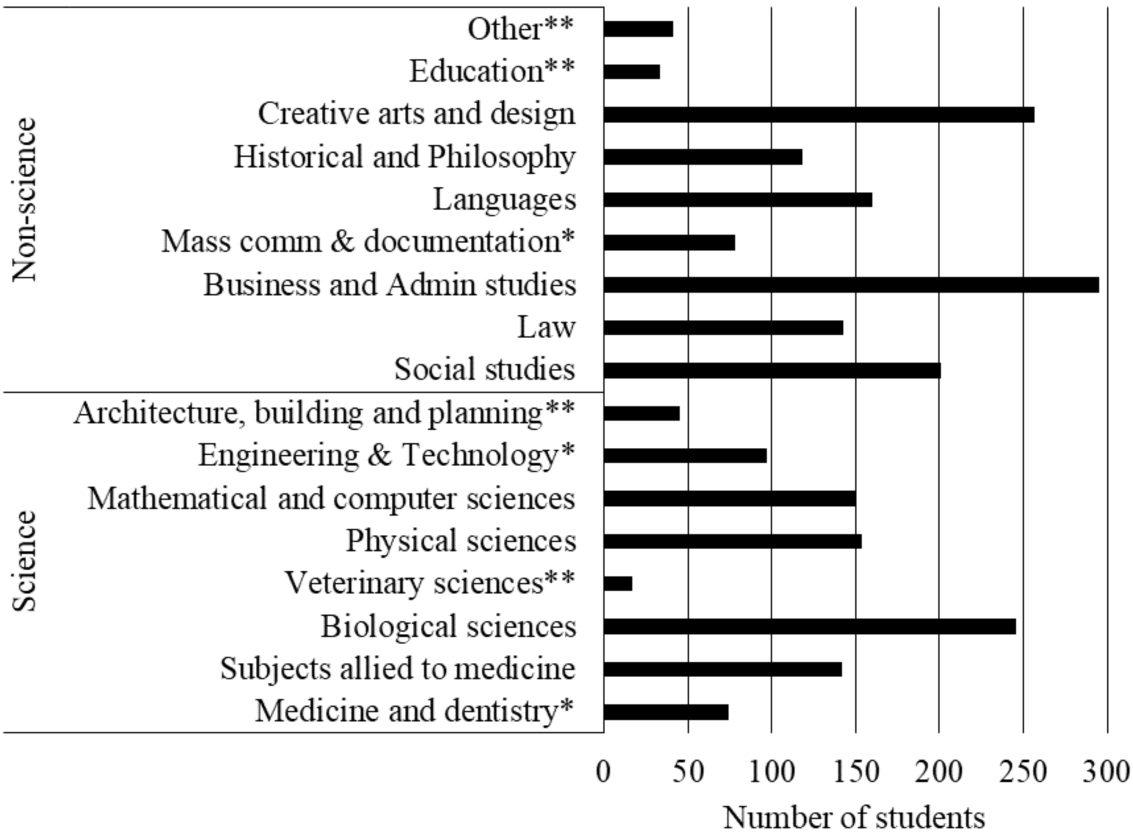
Note: Holidays here refer to Summer, Christmas and Easter. The main variables used in the baseline estimates are marked by the asterisk*.

Table A3.3: Average characteristics of working students by sex in the APS 2010

	Male (%)	Female (%)
Full sample of university students		
Still attending course (in term-time)	81.4	81.3
Average age	19.9	19.9
In paid employment	28.4	35.3
Country of residence		
England	83.7	82.0
Wales	5.3	5.2
Scotland	8.6	9.5
Scotland North of Caledonian Canal	0.1	0.3
Northern Ireland	2.3	3.0
Observations	1911	1901
University students in paid employment		
In part-time employment	86.6	92.4
Total usual hours in main job as according to reference week	17.7	14.9
Type of occupation		
Managers and Senior Officials	2.5	1.1
Professional occupations	3.1	2.4
Associate Professional and Technical	8.4	5.5
Administrative and Secretarial	5.5	6.8
Skilled Trades Occupations	2.8	0.8
Personal Service Occupations	5.0	10.2
Sales and Customer Service Occupations	33.3	40.2
Process, Plant and Machine Operatives	1.9	0.6
Elementary Occupations	37.6	32.4
Type of industry		
Agriculture, forestry and fishing	0.3	0.0
Energy and water	0.2	0.3
Manufacturing	2.5	1.3
Construction	1.9	0.2
Distribution, hotels and restaurants	65.7	67.9
Transport and communication	4.2	1.9
Banking and finance	6.3	5.3
Public admin, education and health	8.7	14.3
Other services	10.3	8.8
Observations	541	678

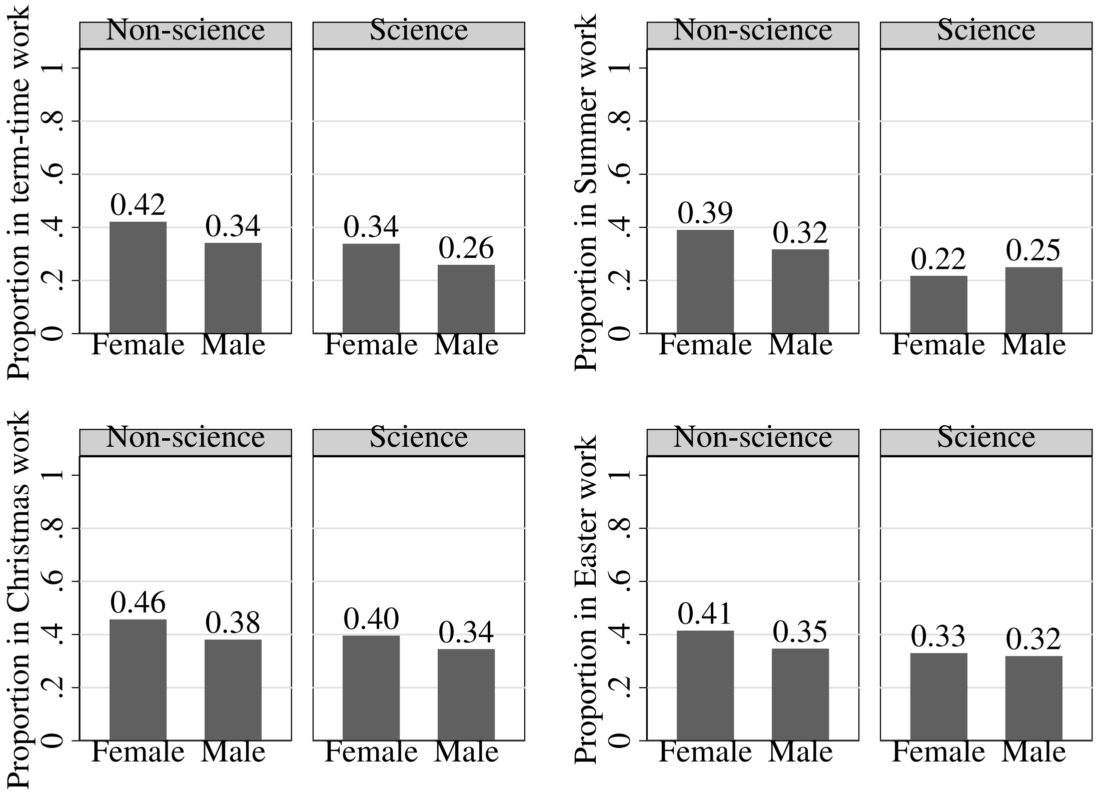
Note: Data sourced from the Annual Population Survey 2010 (ONS 2017).

Figure A3.4: Bar charts of the total number of students in each university subject



Note: *Refers to subjects with less than 100 students and **refers to subjects with less than 50 students. Non-science and Science subjects as defined by the HESA.

Figure A3.5: Bar charts showing the proportion of students in paid work by subject and sex



Note: Subjects as defined by the HESA. Subjects included in Science are 1) Medicine and Dentistry 2) Subjects allied to medicine 3) Biological Sciences 4) Veterinary sciences, agriculture and related subjects 5) Physical Sciences 6) Mathematical and computer sciences 7) Engineering 8) Technologies 9) Architecture, building and planning. Subjects in Non-Science are 1) Social Studies 2) Law 3) Business and administrative studies 4) Mass and communications and documentation 5) Linguistics, classics and related subjects 6) European languages, literature and related subjects 7) Eastern, Asiatic, African, American and Australasian languages, literature and related subjects 8) Historical and Philosophical studies 9) Creative arts and design 10) Education.

3.10 Appendix B

3.10.1 Full estimates

Table A3.4: Full estimates of having ever worked on LOC

	(1)	(2)	(3)	(4)
Ever worked during uni	0.084*	0.074*	0.077*	0.085*
	(0.047)	(0.044)	(0.044)	(0.044)
Sex: Male	0.187***	0.152***	0.154***	0.145***
	(0.049)	(0.048)	(0.048)	(0.047)
Ethnicity: White	0.010	0.054	0.077	0.085
	(0.060)	(0.053)	(0.053)	(0.053)
Health problem or disability at Wave 7	0.014	-0.034	-0.024	-0.022
	(0.093)	(0.083)	(0.084)	(0.084)
Receives a financial help with university costs	-0.004	-0.018	-0.035	-0.041
	(0.047)	(0.044)	(0.049)	(0.049)
Enrolled in wave 6	0.117**	0.081	0.085	0.077
	(0.058)	(0.056)	(0.056)	(0.056)
Attending a Russell Group University	-0.007	-0.047	-0.049	-0.065
	(0.049)	(0.049)	(0.050)	(0.050)
Main parent has higher education	-0.003	0.037	0.054	0.051
	(0.048)	(0.046)	(0.047)	(0.047)
Lone parent/no parent family	0.084	0.082	0.038	0.046
	(0.064)	(0.059)	(0.068)	(0.068)
Number of siblings	-0.016	-0.017	-0.019	-0.019
	(0.020)	(0.019)	(0.020)	(0.020)
Locus of control, wave 2		0.295***	0.279***	0.276***
		(0.024)	(0.024)	(0.024)
Characteristics at age 14-16				
HH managing quite well with income			-0.008	-0.015
			(0.048)	(0.049)
Ever received EMA			0.019	0.019
			(0.061)	(0.061)
Attitude towards school			0.008*	0.007*
			(0.004)	(0.004)
House owned/mortgage/shared ownership			-0.147*	-0.148*
			(0.078)	(0.078)
Subject at wave 7 by HESA science grouping				0.110**
				(0.045)
Observations	2426	2426	2426	2426

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses. All information are obtained from wave 7 when the young person was aged 20/21 unless otherwise stated. Reference categories used are displayed before the categorical variable. Observations shown is raw sample size, but estimates are obtained using wave 7 population probability weights and accounting for clustering at the school level.

Table A3.5: Full estimates of term-time work on LOC

	(1)	(2)	(3)	(4)
Ever worked during term-time	0.100**	0.100**	0.105**	0.115**
	(0.047)	(0.045)	(0.045)	(0.045)
Sex: Male	0.186***	0.152***	0.155***	0.145***
	(0.050)	(0.048)	(0.048)	(0.048)
Ethnicity: White	0.017	0.059	0.083	0.091*
	(0.059)	(0.053)	(0.053)	(0.053)
Health problem or disability at Wave 7	0.014	-0.034	-0.023	-0.020
	(0.094)	(0.084)	(0.084)	(0.084)
Receives a financial help with university costs	-0.011	-0.024	-0.042	-0.049
	(0.047)	(0.044)	(0.049)	(0.049)
Enrolled in wave 6	0.111*	0.073	0.076	0.068
	(0.058)	(0.055)	(0.056)	(0.055)
Attending a Russell Group University	-0.008	-0.046	-0.049	-0.065
	(0.049)	(0.049)	(0.050)	(0.050)
Main parent has higher education	-0.000	0.039	0.057	0.055
	(0.048)	(0.046)	(0.047)	(0.047)
Lone parent/no parent family	0.079	0.076	0.032	0.040
	(0.064)	(0.059)	(0.068)	(0.068)
Number of siblings	-0.015	-0.016	-0.018	-0.018
	(0.020)	(0.019)	(0.020)	(0.020)
Locus of control, wave 2		0.296***	0.279***	0.276***
		(0.024)	(0.024)	(0.024)
Characteristics at age 14-16				
HH managing quite well with income			-0.003	-0.009
			(0.048)	(0.049)
Ever received EMA			0.024	0.025
			(0.061)	(0.061)
Attitude towards school, age 15/16			0.008*	0.008*
			(0.004)	(0.004)
House owned/mortgage/shared ownership			-0.147*	-0.148*
			(0.078)	(0.078)
Subject at wave 7 by HESA science grouping				0.113**
				(0.045)
Observations	2426	2426	2426	2426

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See notes for Table A3.4 above.

Table A3.6: Full Summer estimates of work experience on LOC

	(1)	(2)	(3)	(4)
Work during Summer	0.078	0.062	0.070	0.081*
	(0.049)	(0.047)	(0.047)	(0.047)
Sex: Male	0.180***	0.146***	0.148***	0.138***
	(0.049)	(0.047)	(0.047)	(0.047)
Ethnicity: White	0.019	0.062	0.085	0.093*
	(0.058)	(0.053)	(0.053)	(0.052)
Health problem or disability at Wave 7	0.011	-0.037	-0.027	-0.024
	(0.094)	(0.084)	(0.085)	(0.084)
Receives a financial help with university costs	-0.008	-0.021	-0.037	-0.044
	(0.047)	(0.044)	(0.049)	(0.049)
Enrolled in wave 6	0.121**	0.085	0.088	0.080
	(0.058)	(0.056)	(0.056)	(0.056)
Attending a Russell Group University	-0.006	-0.047	-0.050	-0.065
	(0.050)	(0.050)	(0.050)	(0.051)
Main parent has higher education	-0.001	0.038	0.055	0.053
	(0.048)	(0.046)	(0.047)	(0.047)
Lone parent/no parent family	0.081	0.079	0.036	0.044
	(0.064)	(0.060)	(0.068)	(0.069)
Number of siblings	-0.016	-0.017	-0.019	-0.019
	(0.020)	(0.019)	(0.020)	(0.020)
Locus of control, wave 2		0.295***	0.278***	0.275***
		(0.024)	(0.024)	(0.024)
Characteristics at age 14-16				
HH managing quite well with income			-0.006	-0.013
			(0.049)	(0.049)
Ever received EMA			0.020	0.020
			(0.061)	(0.061)
Attitude towards school			0.008*	0.008*
			(0.004)	(0.004)
House owned/mortgage/shared ownership			-0.143*	-0.144*
			(0.078)	(0.079)
Subject at wave 7 by HESA science grouping				0.111**
				(0.045)
Observations	2426	2426	2426	2426

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See notes for Table A3.4 above.

Table A3.7: Full Christmas estimates of work experience on LOC

	(1)	(2)	(3)	(4)
Worked during Christmas	0.047	0.038	0.043	0.048
	(0.051)	(0.046)	(0.045)	(0.045)
Sex: Male	0.201***	0.168***	0.171***	0.157***
	(0.052)	(0.050)	(0.050)	(0.049)
Ethnicity: White	0.008	0.047	0.074	0.084
	(0.063)	(0.056)	(0.056)	(0.056)
Health problem or disability at Wave 7	0.001	-0.045	-0.038	-0.037
	(0.095)	(0.084)	(0.085)	(0.084)
Receives a financial help with university costs	-0.010	-0.015	-0.040	-0.049
	(0.050)	(0.047)	(0.051)	(0.051)
Enrolled in wave 6	0.115*	0.071	0.076	0.069
	(0.060)	(0.058)	(0.059)	(0.058)
Attending a Russell Group University	-0.009	-0.046	-0.048	-0.069
	(0.053)	(0.052)	(0.053)	(0.053)
Main parent has higher education	-0.032	0.017	0.037	0.034
	(0.051)	(0.049)	(0.050)	(0.051)
Lone parent/no parent family	0.093	0.085	0.035	0.047
	(0.068)	(0.062)	(0.070)	(0.071)
Number of siblings	-0.009	-0.012	-0.014	-0.014
	(0.021)	(0.020)	(0.021)	(0.021)
Locus of control, wave 2		0.299***	0.283***	0.280***
		(0.024)	(0.025)	(0.024)
Characteristics at age 14-16				
HH managing quite well with income			-0.005	-0.013
			(0.049)	(0.050)
Ever received EMA			0.040	0.044
			(0.063)	(0.063)
Attitude towards school			0.008*	0.007
			(0.004)	(0.005)
House owned/mortgage/shared ownership			-0.146*	-0.147*
			(0.081)	(0.081)
Subject at wave 7 by HESA science grouping				0.135***
				(0.047)
Observations	2230	2230	2230	2230

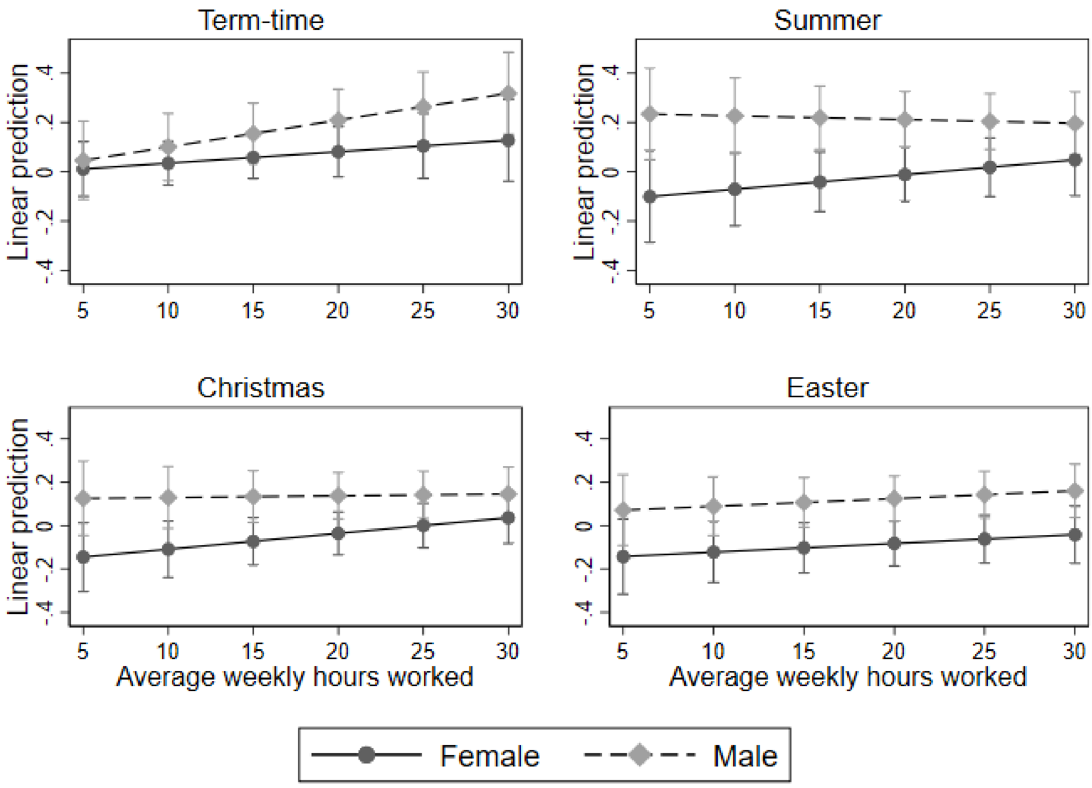
Note: * p < 0.1, ** p < 0.05, *** p < 0.01. See notes for Table A3.4 above.

Table A3.8: Full Easter estimates of work experience on LOC

	(1)	(2)	(3)	(4)
Worked during Easter	-0.002	-0.009	-0.003	0.003
	(0.048)	(0.046)	(0.046)	(0.045)
Sex: Male	0.197***	0.165***	0.168***	0.153***
	(0.052)	(0.050)	(0.049)	(0.049)
Ethnicity: White	0.014	0.053	0.078	0.089
	(0.062)	(0.056)	(0.056)	(0.055)
Health problem or disability at Wave 7	-0.004	-0.050	-0.043	-0.042
	(0.095)	(0.084)	(0.084)	(0.084)
Receives a financial help with university costs	-0.010	-0.015	-0.038	-0.047
	(0.050)	(0.047)	(0.051)	(0.051)
Enrolled in wave 6	0.118**	0.075	0.079	0.072
	(0.060)	(0.058)	(0.059)	(0.058)
Attending a Russell Group University	-0.015	-0.051	-0.054	-0.074
	(0.053)	(0.053)	(0.053)	(0.054)
Main parent has higher education	-0.036	0.013	0.032	0.029
	(0.051)	(0.049)	(0.050)	(0.051)
Lone parent/no parent family	0.094	0.085	0.038	0.050
	(0.068)	(0.062)	(0.071)	(0.071)
Number of siblings	-0.009	-0.012	-0.014	-0.014
	(0.022)	(0.020)	(0.021)	(0.021)
Locus of control, wave 2		0.299***	0.283***	0.280***
		(0.024)	(0.025)	(0.024)
Characteristics at age 14-16				
HH managing quite well with income			-0.003	-0.011
			(0.050)	(0.050)
Ever received EMA			0.038	0.041
			(0.063)	(0.063)
Attitude towards school			0.008*	0.007
			(0.004)	(0.005)
House is owned/on mortgage/shared ownership			-0.143*	-0.144*
			(0.082)	(0.082)
Subject at wave 7 by HESA science grouping				0.133***
				(0.047)
Observations	2230	2230	2230	2230

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See notes for Table A3.4 above.

Figure A3.6: Marginal estimates of average weekly hours spent in work by sex



3.11 Appendix C

3.11.1 Additional checks

Table A3.9: Differences in average characteristics between complete sample and sample which contain at least one missing response to LOC

	Complete (a)	Missing (b)	Diff (a)-(b)
Ever worked	0.52	0.58	-0.057*
Work during term-time	0.32	0.35	-0.030
Work during Summer	0.25	0.30	-0.055**
Worked during Christmas	0.34	0.38	-0.038
Worked during Easter	0.28	0.34	-0.064**
Sex: Male	0.40	0.47	-0.075***
Ethnicity: White	0.58	0.65	-0.065**
Health problem or disability at Wave 7	0.06	0.07	-0.013
Receives a financial help with university costs	0.65	0.62	0.023
Wave enrolled in university	0.74	0.71	0.028
Attending a Russell Group University	0.23	0.26	-0.034
Main parent has higher education	0.38	0.41	-0.031
Lone parent/no parent family	0.16	0.15	0.003
Number of siblings	1.88	1.78	0.104
Observations	2426	593	

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Asterisks indicate the p-values for the t-test in difference of means between the complete sample (a) and the sample excluded (b) because of responses of "Don't know" to at least one item in the locus of control questions.

Table A3.10: Coefficient comparison test on estimates on LOC for having ever engaged in work

	LOC age 20/21			
	(1)	(2)	(3)	(4)
Ever worked	0.084*	0.074*	0.077*	0.085*
	(0.047)	(0.044)	(0.044)	(0.044)
LOC age 15/16		0.295***	0.279***	0.276***
		(0.024)	(0.024)	(0.024)
Propensity to work				
Household managing quite well with income, age 14/15			-0.008	-0.015
			(0.048)	(0.049)
Ever received EMA			0.019	0.019
			(0.061)	(0.061)
Attitude towards school, age 15/16			0.008*	0.007*
			(0.004)	(0.004)
House is owned/on mortgage/shared ownership			-0.147*	-0.148*
			(0.078)	(0.078)
Science subject				0.110**
				(0.045)
Observations	2426	2426	2426	2426

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. All estimates control for sex, ethnicity, long-term health problems, whether received financial help for university costs, enrolled in Russell Group university, main parent's education, family composition and number of siblings.

Table A3.11: Balancing test for main estimates on LOC for having ever engaged in work

	LOC age 15/16	Science subject	HH managing	EMA	Attitude towards school	House owned
Ever worked	0.036	-0.065***	0.011	0.005	0.006	0.023*
	(0.045)	(0.023)	(0.019)	(0.017)	(0.320)	(0.013)
p-values for balancing test						
LHS test: individual	0.418	0.005	0.547	0.775	0.985	0.080
LHS test: joint			0.023			
RHS test: joint			0.016			
Observations	2426	2426	2426	2426	2426	2426

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. All estimates control for sex, ethnicity, long-term health problems, whether received financial help for university costs, enrolled in Russell Group university, main parent's education, family composition and number of siblings. The joint LHS balancing test is conducted via the suest Stata command.

3.11.2 Sensitivity checks

Table A3.12: Estimates with most constrained sample

	Ever worked	Term-time	Summer	Christmas	Easter
Ever worked	0.057	0.073	0.095**	0.043	-0.003
	(0.045)	(0.050)	(0.048)	(0.045)	(0.046)
LOC age 15/16	0.283***	0.283***	0.281***	0.283***	0.283***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)
Observations	2230	2230	2230	2230	2230

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are reported in parentheses. All estimates control for individual characteristics, family characteristics, and propensity to work characteristics. Observations shown is raw sample size, but estimates are obtained using wave 7 population probability weights and accounting for clustering at the school level.

Table A3.13: Estimates with "Don't know" in LOC as a mid-response

	Ever	Term-time	Summer	Christmas	Easter
Ever worked	0.087**	0.090**	0.075*	0.066	-0.001
	(0.039)	(0.041)	(0.041)	(0.042)	(0.043)
LOC age 15/16	0.245***	0.246***	0.245***	0.253***	0.253***
	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)
Observations	3019	3019	3019	2775	2775

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. See notes for Table A3.12.

Table A3.14: Baseline estimates using sum scores of locus of control

	Ever	Term-time	Summer	Christmas	Easter
Ever worked	0.138*	0.178**	0.146*	0.109	0.023
	(0.074)	(0.074)	(0.079)	(0.077)	(0.075)
LOC age 15/16	0.281***	0.281***	0.281***	0.276***	0.277***
	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)
Observations	2426	2426	2426	2230	2230

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. See notes for Table A3.12.

Table A3.15: Baseline estimates, using multiple imputation

	Ever	Term-time	Summer	Christmas	Easter
Worked	0.097**	0.101***	0.084**	-0.041	-0.044
	(0.039)	(0.037)	(0.041)	(0.049)	(0.051)
LOC age 15/16	0.241***	0.241***	0.241***	0.180***	0.179***
	(0.021)	(0.021)	(0.021)	(0.033)	(0.033)
Observations	3,543	3,543	3,543	3,217	3,217

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. See notes for Table A3.12.

Table A3.16: Probit estimates of predictors of probability of engage in work at wave 7

	Ever	Term-time	Summer	Christmas	Easter
Locus of control wave 2	0.026	0.011	0.058*	0.013	0.023
	(0.029)	(0.030)	(0.032)	(0.033)	(0.032)
Sex: Male	-0.305***	-0.232***	-0.099*	-0.216***	-0.182***
	(0.056)	(0.058)	(0.060)	(0.060)	(0.063)
Ethnicity: White	0.373***	0.145*	0.130*	0.282***	0.283***
	(0.075)	(0.080)	(0.075)	(0.082)	(0.078)
Health problem or disability	-0.266**	-0.252**	-0.238*	-0.304**	-0.305**
	(0.121)	(0.121)	(0.132)	(0.134)	(0.128)
Receives a financial help with university costs	-0.111	0.101	-0.027	0.113	0.006
	(0.078)	(0.074)	(0.075)	(0.078)	(0.086)
Wave enrolled in university	0.254***	0.428***	0.161**	0.163**	0.160**
	(0.070)	(0.071)	(0.071)	(0.078)	(0.071)
Attending a Russell Group University	-0.359***	-0.291***	-0.469***	-0.357***	-0.277***
	(0.075)	(0.078)	(0.078)	(0.076)	(0.080)
Main parent has higher education	-0.137**	-0.190***	-0.227***	-0.295***	-0.259***
	(0.068)	(0.067)	(0.072)	(0.074)	(0.074)
Lone parent/no parent family	0.050	0.187*	0.116	0.143	0.033
	(0.093)	(0.097)	(0.091)	(0.098)	(0.101)
Number of siblings	-0.001	-0.015	-0.004	0.008	-0.016
	(0.028)	(0.029)	(0.028)	(0.030)	(0.029)
Household managing quite well with income, age 14/15	0.025	-0.130*	-0.045	0.102	0.045
	(0.065)	(0.068)	(0.071)	(0.071)	(0.073)
Ever received EMA	0.045	-0.095	0.019	-0.146*	-0.145
	(0.081)	(0.083)	(0.084)	(0.086)	(0.090)
Attitude towards school, age 15/16	-0.001	-0.005	-0.013**	0.003	-0.005
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
House is owned/on mortgage/shared ownership	0.170*	0.132	0.064	0.176*	0.104
	(0.095)	(0.104)	(0.100)	(0.107)	(0.108)
Observations	2426	2426	2426	2230	2230

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are reported in parentheses. Receiving help with university costs refers to receiving a grant, bursary or scholarship. Main parent's SOC: high refers to managerial, professional, or associate professional. All information are obtained from wave 7 when the young person was aged 20/21 unless otherwise stated. Observations shown is raw sample size, but estimates are obtained using wave 7 population probability weights and accounting for clustering at the school level.

Chapter 4

Is more screen time bad for adolescent mental wellbeing?

Abstract

Research has provided contradictory findings about whether more screen time is bad for adolescents' mental wellbeing because it had used different definitions of screen time, different measures of wellbeing, and examined different groups of teenagers. This study distinguishes four types of screen activity; social screen time, internet browsing, playing e-games or passive video viewing. I examine whether more screen time is bad for adolescent mental wellbeing, measured by self-reported happiness and self-esteem, and parent-reported behavioural problems of the child. Using time diaries of 14-year-olds, I examine these relationships using models that control for adolescents' prior mental wellbeing and extensive background characteristics, and I show how these relationships differ by gender and parental education. More screen time is associated with lower self-reported self-esteem and happiness with looks. Spending more time on social screen activities and internet browsing are the activities most adversely associated with adolescent wellbeing, compared to playing e-games and passive video viewing. However, social screen time is not associated with worse parent-reported behavioural scores, suggesting that discrepancy between self- and parent-reports may measure different wellbeing scores or that parents under-report on adolescents' wellbeing at age 14. I find support that these relationships are negative and monotonic, and excessive social screen time are associated with worse self-reported mental wellbeing. More screen time is worse for girls' self-reported wellbeing than boys, and this gap is not improved by parental education. Girls with high parental education have worse wellbeing associated with more social screen time, and this gap is largest compared to boys with low parental education.

4.1 Introduction

There has been a rapid rise in digital device use among children and adolescents in the last two decades. Internet use among 12 to 15 year olds in the United Kingdom (UK) more than doubled from 8 hours a week in 2005 to 18.6 hours a week in 2015, with mobile phone and tablets being more popular devices for internet access than computers (Ofcom 2015). At the same time, a National Health Service (NHS) report in 2017 showed that England had witnessed a rise in the prevalence of 'mental disorders' in children aged 5 to 15 years, from 9.7% in 1999 to 11% in 2017 (Sadler et al. 2017). In the NHS 2021 follow-up survey, 39% of those aged 6 to 16 years had experienced a deterioration in mental health since 2017, with girls more likely to experience a deterioration in mental health than boys at the same age (Newlove-Delgado et al. 2017).

Adolescence is a period of dynamic brain development and exposure to stimuli, which is important for adolescents' skills acquisition and emotional processing (Andersen and Teicher 2006; Dahl et al. 2018). Substantial biological, psychological and social development during this period makes adolescence a sensitive period for social development, self-perception, and social interaction. For example, going through puberty is associated with physical maturation, linked with social cognition and peer relations (Pfeifer and Allen 2021). Coupled with the fact that adolescents are also early adopters of new technologies (Dahl et al. 2018) which influence the way they interact with society, screen use can have profound influence on their mental wellbeing as they are often more attuned to how they are perceived by peers and the broader community. Hence, there are heightened parental and societal concerns about media content on screens and adolescent wellbeing, in relation to the 'Displacement Hypothesis' that more time on screen displaces other important activities. There are also concerns that certain screen uses which involve interaction with others such as social networking sites, e-gaming, and internet browsing, may negatively impact adolescents' self-image and happiness because of upward social comparisons (Booker, Kelly, and Sacker 2018; McNamee, Mendolia, and Yerokhin 2021; Kelly et al. 2019). Despite growing research examining the relationships between screen use and wellbeing, studies have reported mixed findings because of the use of different definitions of screen time, and measures of wellbeing, and different groups and characteristics of teenagers.

Previous studies have shown that there are inequalities in screen use and wellbeing across gender and socio-economic status. Adolescents from poorer socio-economic backgrounds have less access to digital devices (Livingstone et al. 2011; Livingstone et al. 2015) and less educated parents in the European Union (EU) also place more authoritative restrictions on their children's device use, while higher income and more educated families use more diverse ways to mediate their children's device use (e.g., pay for other outdoor activities) (Livingstone et al. 2015). Extant literature also show that screen use is typically gendered (girls tend to use social networking sites and text, while boys spend more time gaming (Mullan 2018)), and that screen use is associated more negatively with girls than with boys (Booker, Kelly, and Sacker 2018; McNamee, Mendolia, and Yerokhin 2021; Kelly et al. 2019). However, few studies examine the interaction between both; how the associations differ between girls and boys of high and low socio-economic backgrounds. While girls may be more vulnerable to harmful content on screens, higher socio-economic background may be a protective factor for girls. On the other hand, having more resources may afford adolescents greater access and frequency to screens, exposing them to more harm, and allow different behavioural usage compared to adolescents with lower resources (e.g., more content sharing).

My research examines whether more screen time is bad for adolescents' wellbeing by using detailed information on screen use using time use diaries (TUD) and comprehensive measures of wellbeing, and examine how these relationships vary by both parental education and gender. I examine four questions: 1) Which screen activity is worse for adolescent wellbeing? By examining specific types of screen activities, this study examines whether there are certain screen activities which may have differing associations with adolescents' wellbeing. 2) Do the relationships vary depending on the types of wellbeing measures? Parents may observe behaviour from their child that is not observed through the child's self-reports. At age 14, it may also be that the child's report of their own wellbeing is more accurate than their parents' report of their behaviour, as studies show that observers tend to understate children's mental health as children get older (Johnston et al. 2014). 3) How do these relationships vary by both gender and parental education? The current knowledge is that girls are more vulnerable than boys, but higher parental education may be a protective factor in terms of resources and parenting, and 4) Does excessive screen time equate to worse mental wellbeing? The majority of studies assume a more-is-worse relationship, not accounting that there may be potentially beneficial or neutral levels of screen use.

I answer these questions using the Millennium Cohort Study (MCS), a longitudinal UK study of a cohort of children born in 2000/2001. I use TUD of adolescents who were 14-years-old in 2015, a crucial age because half of mental health illnesses begin at age 14 in OECD countries (Burns and Gottschalk 2019). Adolescents at this age are also undergoing physical pubertal change, have enhanced sensation-seeking behaviour, and are developing their adult identity through interactions with family, cultural, and social contexts (Dahl et al. 2018). Hence, examining adolescents' self concept i.e., their evaluation of themselves (the ideal self), and their identity, family status, personal goals and self-esteem are important.

This study's main contribution is its comprehensive documentation of the relationships between screen time and mental wellbeing, and how these vary with different measures of screen use and wellbeing measures. I use detailed information of screen use from TUD, allowing me to differentiate between social screen time, internet browsing, playing e-games, and passive video viewing in contrast to previous studies which bundle screen use as one activity, and typically use retrospectively reported information which are more susceptible to recall bias and social desirability bias. Each of these types of screen activities is commonly analysed in the previous literature, but are rarely distinguished within one analysis, important to distinguish since each activity requires different levels of attention and provides different levels of exposure of the adolescent to other people and content.

Three additional contributions of this study are the following. First, I demonstrate the importance of distinguishing between adolescent's self-reports and parental reports, and I find that most associations between screen use and wellbeing are mostly captured by self-reports. Both parent and adolescent self-reports are commonly used in previous studies, but rarely distinguished from each other. Second, I add to scant evidence about the variations in these associations by both the adolescent's sex, and parental education as a measure of socio-economic background. Lastly, I test whether the relationships between screen time and wellbeing follows the ‘Displacement Hypothesis’ i.e., more-is-worse, or whether the relationship follows the ‘Goldilocks Hypothesis’ whereby there are levels of screen use that are ‘just right’ or even beneficial for mental wellbeing. This differs from the majority of previous studies, which have tended to assume a negative and monotonic relationship between screen use and wellbeing (Przybylski and Weinstein 2017).

My findings show a division in screen time by sex; girls spend more time on social screen time while boys play more e-games. Adolescents with low parental education spend more hours on screen activities compared to adolescents with high parental education, but the rates of engagement in screen activities are similar across groups. I do not find differences in parenting style and device ownership by parental education. Adolescents who spend more than 3.8 hours on screen time on a weekday and more than 5 hours on a weekend are less likely to spend time on physical activity, educational activities, leisure alone or leisure with others.

My regression estimates show that more time spent on any screen is adversely associated with self-esteem and happiness with looks. The coefficient estimates from more hours on social screen activities and internet browsing with mental wellbeing are larger than the estimates from more hours spent playing e-games or passive video viewing. The harmful associations of social screen time with self-reported mental wellbeing are worse for girls than boys but there are no gender gaps in the parent-reported SDQ scores. More social screen time is also associated with worse self-reported mental wellbeing for high SES adolescents than low SES adolescents, but not for parent-reported behavioural problems. Instead for parent-reported scores, more hours spent browsing the internet and playing e-games are associated with poorer total difficulties score and internalising behaviour for high SES adolescents. Finally, I find overall support for a more-is-worse relationship between screen use and self-reported mental wellbeing. Particularly, excessive hours of social screen time are associated with poorer mental wellbeing. It is worth noting that since Watts (2020) highlighted that Covid-19 has exacerbated the digital divide in the UK, where lack of access to digital technology has consequences for wellbeing and mental health, and the ability to access healthcare. Given that screen use has been increasing, and is likely to continue increasing across time, my findings regarding 2015 provide relevant lower bound estimates of screen use and adolescent wellbeing that are likely to have been accentuated since 2015.

4.2 Background on screen time and adolescent wellbeing

4.2.1 Prior literature

There are numerous studies and literature reviews in the fields of science, psychology, and social sciences analysing screen time and adolescents' mental wellbeing. A common theme discussed in the reviews is that the findings are inconclusive because there is a lack of a standardised definition of screen time, and studies use different measures of wellbeing and examine different groups of adolescents (see e.g., reviews of the literature by Orben (2020), Stiglic and Viner (2019), Dickson et al. (2018), Hoare et al. (2016), and Best, Manktelow, and Taylor (2014)). Screen time is usually self-reported and can refer to a singular activity such as watching TV (Chadi and Hoffman 2021), or the internet (Mcdool et al. 2020), playing video games (Przybylski and Weinstein 2019), or using social media (Booker, Kelly, and Sacker 2018; Kelly et al. 2019; McNamee, Mendolia, and Yerokhin 2021).

In addition, wellbeing measures also vary from mental health disorders (e.g., depressive symptoms, suicide) to more general wellbeing measures (e.g., the Strengths and Difficulties Questionnaire (SDQ), happiness measures, self-esteem) or a mix of these outcomes.

Most research focuses on the hours spent on one specified screen activity, rarely distinguishing between the different types of screen activities within one analysis, as in this paper. Not distinguishing between the types of screen use may lead to missing different associations with wellbeing. For example, Bickham, Hswen, and Rich (2015) used time diaries for students aged 12 to 15 in the USA, and found that mobile phone use and TV viewing were associated with depressive symptoms a year later, but this was not the case for activities such as listening to music, playing video games and using computers. However, the study by Bickham, Hswen, and Rich (2015) is limited to a small sample size of 126 adolescents. Kandola et al. (2022) argued that many studies do not distinguish between screen activities, and show using the MCS data that while replacing an hour of social media or television with team sports was associated with lower emotional distress in adolescents three years later, there were no significant associations from more time on video games or general computer use.

In the next subsection, I will describe how screen activities relate to adolescents' mental wellbeing according to previous empirical research. In doing so, each activity touches on the issue of the content of the screen activity, and how more time on screens influences overall adolescent time use patterns (e.g., increased sedentary behaviour) which may influence mental wellbeing. I distinguish between social screen time, internet browsing, playing e-games and passive video viewing because each activity requires a different attention span and levels of engagement with others, and promotes varied types of content.

4.2.2 How screen activities relate to mental wellbeing

Internet browsing and social media

Internet browsing and social media use involve greater social interactions with other people than watching videos or playing games. Adolescents may gain opportunities for improved mental wellbeing through increased social support, widening social networks and connections, accessing global information, and freedom of expression (Berryman, Ferguson, and Negy 2018; Best, Manktelow, and Taylor 2014; Livingstone, Mascheroni, and Staksrud 2018). On the flipside, adolescents are also at risk of being exposed to harmful content such as pornography, sharing messages with sexual content, fake news and violence, or exposure to cyber-bullying or peer pressure (Best, Manktelow, and Taylor 2014). For UK adolescents aged 10 to 15, Mcdool et al. (2020) found that time spent online was inversely related to their happiness with their school work, appearance, family, school and life overall. The authors found that these negative associations were also stronger for girls than boys, with the largest effect being associated with unhappiness with their appearance. However, Mcdool et al. (2020) examined internet use more broadly, and found that a key mechanism in the relationship between internet use and wellbeing was from excessive social media use.

Social media has been a recent focus in the literature on screen time because it is a more mobile, immersive and continuous form of screen time (see Orben (2020)). Social media are distinct from internet browsing in that they tend to be image-based platforms, e.g. Instagram and Facebook, which allow high frequencies of image sharing and quick image-manipulation techniques. Scholars have argued that social media exacerbates social comparisons, that is, a behaviour where people compare themselves with others to evaluate their emotions, personalities, and opinions and abilities (Festinger 1954; Appel, Gerlach, and Crusius 2016). Often in social media, these social comparisons tend to be upward, i.e., the comparison of one self to someone else who is perceived to be in a better position than one self (Appel, Gerlach, and Crusius 2016). This has led to concerns about promoting an 'idealised' body image or lifestyle, which have negative associations with self-esteem and self-image.

Studies using retrospective screen time measures mainly document a negative relationship between social media and parent-reported behavioural problems, happiness measures, and/or self-esteem (Booker, Kelly, and Sacker 2018; McNamee, Mendolia, and Yerokhin 2021) and a higher risk of depressive symptoms (Kelly et al. 2019). Most studies also report greater harmful associations of social media for girls compared to boys (Booker, Kelly, and Sacker 2018; Kelly et al. 2019; McNamee, Mendolia, and Yerokhin 2021). Girls may face the greater burden of harmful content from social media compared to boys because girls tend to be exposed to early sexualisation through peer pressure and the depiction of females in pop culture and the general media (American Psychological Association 2007). In contrast, some studies find no significant, or weak associations between social media and mental wellbeing (Leung 2014; Puukko et al. 2020; Coyne et al. 2020) and even if negative associations are found, these can turn out to be very small (Orben 2020).

There are few studies that have used time diaries. Two studies that use the MCS time diary data of 13-15 year olds have reported opposite findings. Banthorpe et al. (2020) found that more social media use was associated with a greater probability of self harm and depression and lower self-esteem, especially for girls. However, Orben and Przybylski (2019), using time diaries from Ireland, the US and the UK, found little evidence of a negative association between digital-screen engagement, either throughout the day or before bedtime, and adolescent wellbeing. One potential reason for the differences in these findings is that Orben and Przybylski (2019) used a measure of total screen time, while Banthorpe et al. (2020) only examined social media use. It may be that the harmful associations of social media are masked if grouped as part of a total screen use measure.

Studies have also shown that greater internet browsing and social media use crowd out time for activities that promote mental wellbeing such as sleep (Hisler, Twenge, and Krizan 2020), and face-to-face interactions (Twenge, Spitzberg, and Campbell 2019). Using nationally representative data of U.S. adolescents aged 13 to 18 and students just entering college, Twenge, Spitzberg, and Campbell (2019) documented birth cohort differences across the period 1976 to 2017 and found that adolescents of the 2010s spent less time interacting with their peers in-person and were more likely to experience loneliness during the time that digital media usage increased. Hisler, Twenge, and Krizan (2020), using the MCS data, found that heavy users (self-reported) of screen time were more likely to sleep less, especially during the nights before school. The authors found that social media and internet use were more strongly associated with shortened sleep duration than gaming or TV use, possibly because they involve more social interaction with other people, or are typically carried out on portable devices that are held closer to the face before sleep, thereby delaying sleep. In contrast, Orben and Przybylski (2020) re-examined this relationship using time use diaries for MCS and found that screen use before bedtime was not substantively associated with hours of sleep.

Playing e-games and passive video viewing

Concerns about gaming and video viewing (watching TV) have some overlaps. Studies have found links between excessive time spent on TV and gaming, such as being exposed to violent content, and exhibiting greater aggressive behaviour and worse prosocial behaviour (Anderson et al. 2010; Mitrofan, Paul, and Spencer 2009). However, gaming is distinct from watching videos in that it requires active engagement with the game, which usually involves some level of motor function. It can be a way to train healthy habits of the mind, reward-ing communication and cooperation, as well as resolving negative emotions and frustration (Granic, Lobel, and Engels 2014; Santini et al. 2020). While evidence on the positive link between gaming and wellbeing is lacking, some studies have found no statistically significant associations between violent and non-violent gaming and adolescent aggression (e.g., see Ferguson (2015) and Przybylski and Weinstein (2019)).

An additional concern about watching TV is that studies suppose that more time spent watching TV leads to higher amounts of sedentary time (Hoare et al. 2016), and/or less healthy diets (Stiglic and Viner 2019), which is associated with poorer mental health. While many screen activities such as internet browsing and playing games are linked to more sedentary behaviour the majority of this evidence is for watching TV (Hoare et al. 2016). Nieto and Suhrcke (2021) exploited a policy change in the UK between 2008 and 2012, where the government upgraded every TV transmitter in the UK to switch the transmission of an analogue signal to a high-power digital signal. The switchover raised the number of free television channels from 5 to 40, and led to an increase in the time 10 to 15 year olds spent watching TV. Using an event study model, the authors found that the rise in time spent watching TV worsened adolescents' mental health, measured by parent-reported problematic behaviours of the child. The authors suggested that the main mechanism for worsening mental health was through an increased body mass index due to more sedentary behaviour, but they did not find differences by socio-economic status, gender or ethnicity. Despite the paucity of evidence, Kandola et al. (2020) showed that sedentary behaviour can be related to poorer mental wellbeing. Using a large population-based sample of adolescents in South-West England, the authors demonstrated that an additional hour of sedentary behaviour was associated with an 8 to 11% increase in depression scores for adolescents aged 18 years.

Shape of the relationship between screen use and wellbeing

All of the findings described above assume a more-is-worse relationship with each of the screen activities, which may not be true. In contrast, the 'Goldilocks Hypothesis' which was first coined by Przybylski and Weinstein (2017), posits that there may be a level of screen time that is 'just right'. The authors argue that 'too little' screen time reflects adolescent deprivation of social information whereas ‘too much’ may lead to displacing beneficial activities. The authors show that for English 15-year-olds, moderate amounts of self-reported screen time are associated with higher mental wellbeing compared to very low or very high levels of screen time. Research using self-reported screen time shows support for it (McNamee, Mendolia, and Yerokhin 2021), but studies that use time diaries do not (Sanders et al. 2019).

4.2.3 Differential associations of screen time and well-being by sex and socio-economic background

Gender

As discussed above, girls usually face greater stresses and pressures from screen use compared to boys, such as sexualised ideals of women, which impose more pressure in regard to body image and self-esteem,. Although studies have found that boys spend more time on digital activities than girls (B. Becker 2022; Gracia et al. 2022), the greater online risk for girls may lead to girls facing greater harm from screen use in relation to their mental wellbeing. This may also be driven by how the screen time is used. For instance, a study of adolescents aged 13 to 17 in the USA in 2015 by Lenhart (2015b) showed that boys use e-gaming as a platform for friendships while girls use social media and texting, which compared to e-gaming has more challenges (e.g., girls are more likely to block friends).

There is limited research about how these gender gaps in adolescents’ time allocation relate to their social and emotional competencies or mental wellbeing. Jürges and Khanam (2021) find that although boys spend more time in front of screens, more screen time instead of physical activity has a greater negative impact on girls’ social and emotional competencies than boys. Using the same data, Nguyen et al. (2022) find that Australian teenage girls spend more time doing chores, on their personal care, and on educational activities outside of school while boys spend more time on physical and screen activities compared to girls. In contrast to Jürges and Khanam (2021), the authors show that these differences in time allocation account for gender gaps in the development of cognitive skills and social and emotional competencies, favouring girls. Educational activities outside school explain for up to 15% of the gender gap in cognitive skills and screen activities contribute to 3% of the gender gap in social and emotional competencies. These studies show how variations in time use are relevant for adolescents' outcomes, but there is a gap in our knowledge about how these relationships work, and their application across different countries.

Socio-economic background

The literature discusses three 'levels' of digital divides across the population; (1) the unequal access to screens or information and communications technology (ICT), (2) unequal online and digital 'skills' and divergent forms of engagement, and (3) multiple outcomes that stem from dissimilar social and digital contexts (Maggio et al. 2004; Hargittai 2008; Helsper 2021). To date, there has been little systematic analysis of how changes in digital engagement relates to wellbeing across socio-economic groups, especially with regards to levels two and three (Gracia, Bohnert, and Celik 2023). Studies have found that adolescents from lower socio-economic backgrounds, compared to higher socio-economic backgrounds, spend higher amounts of time on screen-based activities, experience more negative feelings during their online activities, and have scarcer economic, social, cultural and digital resources to help secure a healthy and productive engagement with screens (Gracia et al. 2020; Helsper 2021; Ragnedda 2018).

However, it is also possible that adolescents from higher socio-economic backgrounds may be exposed to more risk of harmful content because they have better access to the internet and digital technologies and hence have greater engagement with screen use (Livingstone et al. 2015). In their study of 9-16 year olds in 25 countries, Livingstone et al. (2011) found that children from higher socio-economic homes are more likely to have a wider, more diverse circle of contacts online, including more people they do not know offline, but it is unclear whether this relates to greater risk. The authors also find that children from higher socio-economic homes compared to lower ones, are more likely to see online sexual images and to receive more sexual messages online, but, this exposure to risk may not relate subjective harm (Livingstone et al. 2011). On the flipside, Lenhart (2015a) have also shown that lower income teenagers are more likely to have the same friends over multiple social media platforms, which may mean they are more selective of who they interact with because they have more limited access to these technologies.

It may also be that socio-economic backgrounds may drive different types of technology usage. For example, Lenhart (2015a) showed that youth from higher income groups in 2015 were more likely to use Snapchat and Instagram, while youth from lower income groups were more likely to use Facebook. While all these platforms allow self-promotion and encourage upward social comparisons (general impression that someone else is better off), Snapchat and Instagram are more likely to promote such comparisons at a higher frequency than Facebook.

Lastly, a recent study in the UK showed that the association between social media and mental wellbeing, depression and anxiety depends on the adolescents' behavioural use of the platform. Winstone et al. (2022) show that "Broadcaster" users – those who frequently share content in addition to socialising or browsing online – are at greatest risk to their mental wellbeing, compared to minimal users, moderate communicator (moderate messaging and browsing but minimal content sharing) and high communicator groups (frequent messaging and socialising and moderate content sharing and browsing). It may be that adolescents with greater resources are more able to 'broadcast' and interact with content sharing compared to adolescents who have lower resources. Lastly, adolescents with higher educated parents are also likely to be friends with other adolescents that have families with resources, which may fuel a competition for upward comparisons through internet platforms (e.g., family holidays abroad, access to branded goods). While I do not observe the types of content/platforms used, these differences may explain the channels in which there may be differences across demographic groups.

Few studies have examined the inter-relationships between sex and socio-economic status. In this chapter, I explore inequalities by sex and parental education through the digital divide in terms of access (as described in point 1 above), and in usage (point 2), keeping in mind that the context we have are for a selected birth cohort in the UK in 2015. Drawing upon previous literature, it is likely that girls from lower parental education are at greater risk from screen use as it brings a double disadvantage, especially compared to boys with higher parental education. However, there is also the possibility that girls, regardless of parental education, are at greater risk from screen use than boys, since girls are disproportionately exposed to harmful content on screens.

4.2.4 Who reports wellbeing

Finally, there may be differences based on the observer who reports wellbeing (e.g., either by parent or the adolescent). Both scores have been used in previous studies, but few studies distinguish between the two in regard to their findings.

The disagreement between parent and adolescent reports may stem from parents' reporting fewer or more problems than their children report about themselves. Studies have reported that adolescents' ratings yielded higher problem scores than their parents (Petot, Rescorla, and Petot 2011; Rescorla et al. 2013). In a British study using the SDQ, Goodman et al. (2000) suggest that children's self-assessments of their behaviour (before the age of 11) have less explanatory power than parents or teachers. Youngstrom, Findling, and Calabrese (2003) found that using the same data and threshold scores of a clinical sample in the USA of youths aged 11 - 18, there were significant variations about comorbidity prevalence rates based on the observer, ranging between 5.4% and 74.1%. In a UK study about children's mental health and their educational attainment using multiple observers for children and adolescents' behaviour. Johnston et al. (2014) found in the UK, large variations in survey reports of children's mental state across observers. They also found that observers tend to understate children's mental health scores as children get older.

Another factor for low parent-adolescent agreement may be due to the reporting of different kinds of problems. For instance, parents might report similar observable behavioural problems (e.g., externalising issues) as their children, but divergences may occur for more internalising problems as parents may not know how their children are feeling until the adolescent divulges this information (Rescorla et al. 2013). Assessments may also vary by the observer's characteristics. Studies show that there are systematic differences in parent, teacher, and self-reports of adolescent mental health, with greater income-health gradients from adult reports than self-reports (Khanam, Nghiem, and Rahman 2020; Johnston et al. 2014). Using the MCS data, Del Bono, Kinsler, and Pavan (2020) demonstrated that differences in mothers' socio-emotional competencies are related to how children's socio-emotional competencies are reported. In line with this, Hazell et al. (2022) also using the MCS data found that parents' mental health gradient mirrored that of the parent-reported adolescent mental health gradient. While the authors found that adolescents from more disadvantaged groups had poorer ratings of mental health, the magnitude and significance of this health gradient was larger when rated by parents than by adolescents themselves.

4.2.5 Adolescents' screen time in the UK

Examining adolescents' screen time in the UK in 2015 is relevant because children born in the UK during the 2000s have grown up with screens, the internet, and social media. Mullan (2019) documented that children aged 8 to 16 in the UK led less physically active and more home-based lives in 2015 compared to in 2000. He also documented a substantial increase in screen-based activities, positing that rapid technological change had influenced children and adolescents' activities to be more indoors-based. Ofcom (2015) report that in 2015, 12 to 15 year olds in the UK had three or more devices of their own, typically a smartphone, a tablet and a laptop/PC, with few differences by gender or household SES. The report also indicated that YouTube became an important source of content in addition to watching TV. 86% of 12 to 15 year olds in 2015 who watched TV also watched YouTube. Of those who watched both types of content, for the first time in 2015, 29% said they preferred to watch YouTube videos compared to TV channels (25%). This contrasts with in 2014, when 30% preferred to watch TV channels compared to YouTube (25%). Popular social media platforms used by 12 to 15 year olds in 2015 were Facebook, Instagram, Snapchat and YouTube.

There are also strong parental and societal concerns about adolescents' wellbeing and screen use in the UK. Ofcom (2015) have reported that one-third of parents whose child goes online are concerned about online bullying and about a fifth to a quarter of parents are concerned about content viewed on the TV and the internet respectively. These concerns are also highlighted at the policy level, as reflected in reports such as one by the House of Commons (2019), which reviewed studies on the impact of social media and screen use on young people's health. In addition, understanding these relationships for adolescents in 2015 help uncover conservative estimates for us to understand the potential relationships since Covid-19.

4.3 Data and Descriptive Statistics

4.3.1 The Millennium Cohort Study

I use data from the Millennium Cohort Study (MCS), a nationally representative, longitudinal birth cohort survey of individuals born in England and Wales between 1 September 2000 and 31 August 2001, or born in Scotland and Northern Ireland between 24 November 2000 and 11 January 2002. The MCS data has rich information about adolescents, parents, and teachers over seven sweeps. The MCS sample covered children from England, Wales, Scotland and Northern Ireland in the UK who were eligible for child benefit and were 9 months old at the time of the first sweep. It used a stratified, clustered random sample design and oversampled from areas that were disadvantaged or had high ethnic minority populations. Each UK country has an advantaged and disadvantaged strata, and England has an additional "ethnic" strata for ethnic minorities.[1] The first sweep of data was collected when the respondent was 9 months old on average, followed by at ages 3, 5, 7, 11, 14 and 17. Note that in the second sweep of data, so-called 'new families' were introduced because they were eligible for the first MCS sweep but were not identified because their addresses were not recorded on the Child Benefit register. My analysis uses time use diary (TUD) data from the sixth sweep of the MCS data in 2015, when the study participants were aged 14 years old on average. The MCS had an initial sample of 18,818 children who were surveyed in sweep one; this figure had fallen by 60% to 11,884 adolescents in sweep six. To account

[1]To better represent disadvantaged children and ethnic minorities, the MCS oversampled children from deprived background as well as children from areas of relatively high ethnic minority concentration. The original sample was drawn in two stages. The first stage selected the electoral wards and the second stage selected families within those wards. All electoral wards were allocated into one of three types: (1) "ethnic" i.e. wards in England in which 30% or more of the population were Black or Asian as defined in the 1991 Census of the population. (2) "Disadvantaged" i.e. the poorest 25% of wards as defined by the 1998 Child Poverty Index and (3) "Advantaged" which are all other wards not classified as (1) and (2) above.

for the attrition by the sixth wave, I use non-response weights for sweep 6, as discussed in Ketende and Jones (2011).

For the sixth sweep, interview data are available for 11,884 adolescents in the main survey. Only 10,337 adolescents were invited to complete the TUD because of limited activity monitoring devices (administered at the same time as the TUD to measure physical activity), comprising of 100% of the sample in Wales, Scotland, and Northern Ireland and a random sub-sample of approximately 81% of adolescents in England. Of the approximately 10,000 who were eligible, 4,640 adolescents completed and returned the TUD. 3919 answered both the weekend and weekday diaries, 353 only the weekday and 368 only the weekend. When comparing TUD information to other variables of interest, I find that most of the missing information is from adolescents not providing an answer to the first self-completion questionnaire in wave 5 (age 11). Since I cannot determine if this was not answered because they did not know or refused to answer, I restrict my sample to all non-missing relevant variables, which leads to a loss of about 24% of the original sample, resulting in a final sample of 3,416 adolescents, 2954 who answered TUD for both days, 220 on the weekday only and 255 who answered on the weekend only. [2] Despite the small number of achieved cases which was about a third to a quarter of the issued sample, having randomised the sample issued at least attempted to represent the sample by country. However, there can be non-response bias based on returned TUD, as the TUD is likely more cumbersome than the standard questionnaire.

Appendix Table A4.1 shows the differences in age, sex, ethnicity and country (by stratum) for adolescents who have information matched to the time use diaries compared to those whose information was not matched. The matched TUD samples showed similar representation by age, but there is an over-representation of girls (53% compared to 47%), white ethnicity (83% compared to 73%), under-representation of Pakistani and Bangladeshi (6% compared to 8%), and Black or Black British (2% compared to 4%), and similar repre-

[2]For the measures of mental wellbeing used in this analysis, 153 adolescents were missing self-completion information at age 11. This is likely the sample of adolescents who were re-sampled at age 14 who were living abroad but not captured at age 11. In addition, there were 78 and 158 “no answers”, as “don’t know” or “refused to answer” were not provided as response options. 145 adolescents also had missing parent-reported information about their SDQ because parents refused to answer the self-completion questionnaire.

sentation of ethnicity for Indian and Mixed ethnicities, with no to very few cases of missing ethnicity. The matched TUD sample also over-represents adolescents from advantaged stratums in Scotland and Northern Ireland, and under-represented adolescents from disadvantaged and ethnic backgrounds in England.

Given these differences, the analysis from the TUD are more biased towards girls, white ethnic groups, and adolescents from Wales, Scotland and Northern Ireland but still is representative by age compared to the wider cohort study. However, since my analysis uses a cohort study about screen use in 2015, the analysis with or without the response bias from TUD information, do not generalise to other adolescents in the UK. The main contribution of this study is conceptualising the types of screen time in more granular detail with respect to adolescent mental wellbeing, using rich longitudinal information, but these findings are mostly relevant for a cohort of White and relatively advantaged girls.

4.3.2 The Time Use Diaries (TUD)

The TUD provides extensive information about the adolescents' activities in two 24-hour periods, a randomly chosen weekend and weekday. The adolescents were given an option to choose between a web or app mode, and paper was offered only if the adolescent could not complete electronically (no internet access or smartphone) or if they refused to complete via web or app mode. For paper and web based instruments, respondents were provided a timetable of 10-minute slots split throughout 4am and ending at 4am the following day, amounting to a total of 144 slots. In the app modes, respondents were allowed to assign the end time of their activities, which allowed an accuracy to the minute. Please refer to Appendix Figures A4.1 to A4.3 to see examples of how adolescents could record their activities. Adolescents recorded their activity responses from a pre-coded list of 44 activity codes, nested within 12 top-level activity categories. The adolescents were required to provide full details of what they did, as well as where they were, who they were with and how much they liked the activity. Appendix Table A4.2 show the full list of activity codes and grouped activities.

The regular public-use harmonized version of the data standardises all responses from the three modes in a calendar format. For each adolescent, the harmonized data presents 144 rows (24 hours = 144 10-minute slots), where each row represents a 10-min slot beginning from 4:00am, along with an assigned activity to each slot. If there is no recorded activity, the activity is labelled as missing. An example of how these activities are presented are in Appendix Figure A4.4. However, the harmonized version of the time diaries omits information such as who they performed the activity with. I added value to these data using previously unprocessed information. To examine how screen time displaces face-to-face leisure activities, I matched information on who the activity was done with to the harmonized data using the Python code provided in the MCS technical report, creating a new column on who the activity was performed with Veeravalli (2019).

4.3.3 Types of screen time

The TUD provides a list of seven pre-coded screen activities. Of the seven activities, I distinguish four types of screen time, which are summarised in Table 4.1 below. Social screen time includes socially interactive activities that are commonly seen to displace face-to-face interaction. Under the social screen time heading, more time was spent on browsing or updating social networking sites compared to answering emails, texting, video calls, and instant messaging. Internet browsing refers to activities that provide information, but require the user to search for the information. Both internet browsing and social screen time are activities that are commonly said to be related to poorer adolescent self-esteem and self-evaluation because users tend to compare their lives and body image against what global peers post on forums or on social networking sites. Finally, distinguishing between playing e-games and passive video viewing differentiates between an interactive activity that may involve problem solving and can be played with others on the one hand, and more passive video viewing, which may require more sedentary time on the other.

Of the remaining 37 activity codes, I distinguish five additional types of activities that may be displaced by screen time: 5) sleep 6) physical activity and exercise 7) educational activities 8) work/leisure alone and 9) work/leisure with others. Including these five activities allows me to examine differences in the average time spent on other activities for adolescents

Table 4.1: Four types of screen activities

Grouped activities	Second-level coded activites
1. Social screen time	Answering emails, instant messaging, texting
	Speaking on the phone (including Skype, video calls)
	Updating/browsing social networking sites
2. Internet browsing	General internet browsing, programming (excluding social networking sites)
3. Playing e-games	Playing electronic games and apps
4. Passive video viewing	Watching TV, DVDs and downloaded videos

who spend low to excessive amounts of time on screen activities. I also control for these activities in the regression estimates, as adolescents who spend a similar number of hours on screen time may spend different amounts of time on say, physical activity. A full list of these categories and activities can be seen in Table A4.2. Since my data only allow me to examine primary activities, I am unable to examine the content of the devices, nor can I examine any obsessive or addictive behaviours through multitasking. What I do observe is the types of screen activities that proxy engagement with the unobserved content, such as social screen time allowing greater interaction with other people compared to passive video viewing.

4.3.4 Measures of mental wellbeing

Studies have shown that the density of grey matter volume in the amygdala, a structure associated with emotional processing, is related to larger offline and online social networks, suggesting an important relationship between social experiences and brain development. A review by Crone and Konjin (2018) show that adolescents' neural systems are still undergoing significant changes which likely contributes to adolescents' sensitivity to online rejection, acceptance, peer-influence, and emotion-loaded interactions in media-environments. Therefore, we expect that adolescence is a sensitive time for adolescents' wellbeing in relation to screen use because of these influences, especially in situations where adolescent social interactions on screen becomes increasingly commonplace.

Rather than examining mental health disorders, I am interested in adolescents' flourishing wellbeing, which relates to the presence of happiness, having purpose and sense of meaning, and good relationships (Huppert 2009). I use the The UN H6+ Technical Working Group on Adolescent Health and Well-being (Ross et al. 2020) which frames adolescent wellbeing in five domains (please see Chapter 1, Section 1.3.3 for further discussion); (Domain 1) good health and optimum nutrition; (Domain 2) connectedness, positive values, and contribution to society; (Domain 3) safety and a supportive environment; (Domain 4) learning competence, education, skills, and employability; and (Domain 5) agency and resilience. For self-reports, I use self-esteem, which touches on Domain 4 that adolescents have the confidence to do things well, and Domain 5 that they are confident in their identity. I use happiness in six domains; the way they look, friends, family, school, school work, and their life as a whole which encapsulates Domain 2 (interconnectedness with peers, family, and school), Domain 3 (vulnerability of sub-groups in safe spaces on screens), and 5 (sense of identity with happiness with their looks). Lastly, I use parent-reported strengths and difficulties questions (SDQ), widely used emotional and behavioural screening questionnaire for the early detection of mental health disorders amongst young people. This encompasses Domain 1 which includes mental health and capacities. A full list of the items and scores can be seen in Table A4.3.

The SDQ was first developed by Goodman (1997) and is made up of 25 items divided into five scales: emotional symptoms, peer problems, conduct problems, hyperactivity/inattention, and prosocial behaviour. The parents of the adolescents were asked to think about their child's behaviour over the previous six months and rank 25 items related to their child's behaviour on a 3-point scale ("Not true"=0, "Somewhat true"=1, "Certainly true"=2). According to Goodman, Lamping, and Ploubidis (2010), these scales can be further grouped into four groups for general populations, which I use in my analysis. These are 1) internalising behavioural problems as the sum score of emotional symptoms and peer symptoms, 2) externalising behavioural problems as a sum score of hyperactivity/inattention and conduct problems, 3) total behavioural problems which is the sum of scales 1 and 2, and 4) prosocial behaviour. For scales 1 to 3, higher scores indicate worse emotional or behavioural problems. On the other hand, higher scores for prosocial behaviour indicate better behaviour. To maintain consistency in interpreting the wellbeing measures, I reverse-coded the scales 1) to 3) to indicate that higher scores indicate better behaviour i.e. best behaviour is the maximum score, and worst behaviour is coded to 1. Each scale is standardised to have a mean of zero and standard deviation of 1.

Self-esteem is a crucial measure of self-concept during adolescence, especially as adolescents undergo physical pubertal changes around age 14 (Dahl et al. 2018). Studies find that more screen use by adolescents, particularly social media, is associated with poorer self-esteem, body image and happiness with their looks, and argue that adolescents who use social media frequently tend to compare their lives against other users (Kelly et al. 2019; Banthorpe et al. 2020; McNamee, Mendolia, and Yerokhin 2021). The Rosenberg self-esteem scale has five items to measure respondents' level of self-worth, half the number of items compared to the original Rosenberg scale (Rosenberg 1965). The responses to each item range from "Strongly disagree"=1 to "Strongly agree"=4. I run a factor analysis of these items and find that they load onto one factor. I use the predicted value of the factor analysis, and standardise the score to have a mean of zero and standard deviation of 1.

Finally, I measure adolescent happiness ratings in six domains; the way they look, friends, family, school work, the school they go to, and their life as a whole. This measure was first conceptualised by Huebner (1994) to create a multidimensional measure of positive subjective wellbeing for children and adolescents. While happiness with the way they look is more strongly related to self-concepts like self-esteem, happiness with friends, family, school and school work, all reflect healthy peer engagement in environments that adolescents spend most of their time in (Zŭkauskiene 2014). For each domain on the happiness scale, the responses range from "Not at all happy"=1 to "Very happy"=7. Each happiness domain score is standardised to have a mean of zero and a standard deviation of 1.

Table 4.2 lists these wellbeing measures, and provides summary statistics. Columns 2 to 4 report the median, min, and max of each wellbeing measure for the average adolescent. The following columns compare the differences in the means by parental education and sex and the p-values from testing the differences in the means between the groups. A negative score indicates that girls (lower parental education) have lower wellbeing than boys (higher parental education).

I use parental education as a proxy for socio-economic background, measured by a

Table 4.2: Differences in average wellbeing scores by parent education (SES) and sex

	All			Low-	p-val	Girls	p-val
	Median	Min	Max	High		-Boys	
Total Difficulties Score (excl. prosocial)	28.00	1.00	34.00	-1.09	0.00	-0.67	0.00
Internalising behaviour	17.00	1.00	20.00	-0.53	0.00	-0.75	0.00
Emotional symptoms	10.00	1.00	11.00	-0.42	0.00	0.02	0.76
Peer problems	10.00	1.00	11.00	-0.27	0.00	0.39	0.00
Externalising behaviour	17.00	1.00	20.00	-0.84	0.00	0.74	0.00
Hyperactivity/Inattention	9.00	1.00	11.00	-0.56	0.00	0.08	0.25
Conduct problems	9.00	1.00	10.00	-1.26	0.00	0.76	0.00
Prosocial	9.00	0.00	10.00	-2.38	0.00	0.09	0.73
Total rosenberg score	15.00	5.00	20.00	-0.46	0.00	-1.65	0.00
On the whole, I am satisfied with myself	3.00	1.00	4.00	-0.07	0.04	-0.40	0.00
I feel that I have a number of good qualities	3.00	1.00	4.00	-0.11	0.00	-0.35	0.00
I am able to do things as well as most other people	3.00	1.00	4.00	-0.10	0.00	-0.26	0.00
I am a person of value	3.00	1.00	4.00	-0.08	0.00	-0.21	0.00
I feel good about myself	3.00	1.00	4.00	-0.11	0.00	-0.43	0.00
Happiness scores							
Happiness with your school work	6.00	1.00	7.00	-0.26	0.00	-0.15	0.01
Happiness with the way you look	5.00	1.00	7.00	-0.13	0.04	-0.91	0.00
Happiness with your family	6.00	1.00	7.00	-0.04	0.45	-0.23	0.00
Happiness with your friends	6.00	1.00	7.00	0.00	0.95	-0.20	0.00
Happiness with the school you go to	6.00	1.00	7.00	-0.33	0.00	-0.24	0.00
Happiness with your life as a whole	6.00	1.00	7.00	-0.16	0.01	-0.55	0.00

Note: The total difficulties score is a sum score of internalising and externalising behaviour. Internalising behaviour is the sum score of emotional symptoms and peer problems, while externalising behaviour is a sum score of hyperactivity/inattention and conduct problems. These scores were reverse coded to indicate that a higher score reports better behaviour, in the same direction as prosocial behaviour and other self-reported scores.

binary variable equal to 1 if the highest parental education in the household is above the level NVQ4 (equivalent to an undergraduate degree or a full technical certification), and 0 otherwise. I use parental education as the main indicator for socio-economic background because parents with higher education not only have more assets and resources like income, but may also have different views and knowledge about screen use, which may determine how much time their children spend on screens. While I acknowledge that there may be several indicators of socio-economic background, in Appendix Table A4.5 I show that parental education is highly correlated with income and social class.

Most adolescents report relatively high self-esteem measures and happiness levels, and the parent-reported SDQ scores reflect relatively low behavioural problems (reverse-coded, so a high score indicates better behaviour) and high prosocial behaviour. However, adolescents with lower educated parents score worse on their parent-reported behavioural problems and self-reported wellbeing scores compared to adolescents of higher educated parents. Girls have lower self-reported wellbeing scores than boys, but similar scores when comparing parent-reported behavioural problems. Additionally, adolescents report lower happiness about the way they look (median 5), compared to the scores for other domains of happiness (median 6).

4.3.5 Control variables, sex and socio-economic status

There may be several important differences in terms of individual and family-level characteristics in explaining the variation in adolescent mental wellbeing, which I control for in my estimations. I include contemporaneous demographic characteristics of the adolescent and their early childhood family socio-economic background (age 5 and below). Early childhood family socio-economic background is important because parental background is likely to have the greatest effect on children's later development in terms of their time spent with the child and resources (Francesconi and Heckman 2016). I use parental education as defined before, highest social class in the family, and housing tenure, as proxies for family income and wealth in assets, important for digital device ownership and access. I use measures of all these socio-economic background variables at age 5 because they are the earliest measures available that include the 'new families' introduced in the second sweep. To account for the potential transmission of wellbeing through parenting or genetics, I control for their main parent's mental health, measured by the Kessler score.

I control for adolescents' individual characteristics that may determine differences in mental wellbeing such as their age, measured as the difference to 14 years old from the date of interview, because the majority of adolescents in the sample are aged 14; whether they were of "White" ethnicity; the presence of any long-term illness; and their cognitive score measured by the word-activity score as studies have shown that there is a strong cross-production between adolescents' cognitive and wellbeing development (Cunha and Heckman 2008). To account for early behavioural characteristics that may not be influenced directly by screen use, I include early behavioural scores when the adolescents were 9 months. I use the Carey's Infant Temperament Scale (CITS), a widely used parent-report measure of infant temperament. The CITS measures four scores as shown in Appendix Table A4.4, where each score is made up of three items ranked from 1 to 6, except for mood which is made up of five items: mood, approach/withdrawal, adaptability, and regularity.

I also control for family demographics, such as number of siblings at age 14, which may determine device sharing as well as media exposure, mother's age at the birth of the child, and whether both natural parents were in the household, to control for family hardship and parental income/time resource. I control for the disadvantaged and advantaged stratum indicator variables, the number of days of reported TUD, and the mode the TUD was collected (web, app, paper). Finally, I include the adolescent's prior wellbeing scores at age 11 to account for some potential endogeneity in estimating screen use and wellbeing, which I will explain in section 4.4.

Appendix Table A4.6 describes the background characteristics of the adolescents by parental education and sex. The girls and boys seem to have had similar background characteristics. The majority of adolescents answered the TUD through the app, followed by the web and paper mode. There were few differences by parental education, but slightly more girls answered the TUD via app compared to boys. Adolescents with higher parental education (compared to parents with lower education), and boys (compared to girls) had poorer mood scores at 9 months old compared to adolescents with lower educated parents, but had better approach, adaptability and regularity behaviours.

Disadvantaged households were disadvantaged in more than one way. Only 57% of adolescents with low parental education had a natural father in their household at age 14, compared to 80% of adolescents with highly educated parents. Adolescents with low parental education had, on average, more siblings in the household, a lower average word activity score, and younger mothers than their more advantaged peers. Only just over half of adolescents with lower educated parents were likely to own their home or have a mortgage compared to 90% of adolescents with high educated parents. A third of adolescents with low parent education had none/not working as their highest socio-economic class in the household, and a third were in semi-routine/routine jobs, compared to the highly educated parents, where over half of the highest socio-economic class were in managerial and professional jobs.

4.4 Modelling the screen time and wellbeing relationship

I examine the relationship between adolescents' screen time and their wellbeing, using the specification below. For each adolescent at the average age of 14, I estimate:

$$Y = \alpha + \beta S + \gamma I + \delta G + \varepsilon V + \zeta T + \omega M + \eta X_5 + \theta Y_{11} + \iota R + \kappa \tag{4.1}$$

where Y represents one of the three mental wellbeing measures. The screen measures are indicated by social screen time (S), internet browsing (I), playing e-games (G), and passive video viewing (V), respectively. The specification controls for all adolescent demographic characteristics, early behavioural scores at 9 months old (measured by the Carey's Infant Temparament Scale, CITS), early socio-economic status at age 5, and parent characteristics (X_5), are described in Appendix Table A4.6. T is the full vector of "other" time activities such as sleep, physical activity, and so on. I use sleep as the base category in my main specifications. Y_{11} is the adolescent's mental wellbeing measure at age 11, corresponding to the same wellbeing variable interest at age 14, Y. The coefficients β, γ, δ, and ε measures the association of an additional hour of the respective screen time and mental wellbeing, instead of the baseline activity in T, and I use sleep as the baseline activity. M controls for the mode in which the diary was filled in (paper, PC, or app), R is a set of stratum indicator variables to control for regional differences and κ is the error term. Weekday and weekend activities are likely to differ since adolescents aged 14 tend to spend most of their weekdays in school, while weekends give them more freedom for other activities such as leisure, chores and work. Therefore, I fit model 4.1 showing the estimates separately for the weekend and weekday respectively.

I use model 4.1 to answer my research questions as follows. First, I examine whether an additional hour of each screen activity instead of sleep is associated with greater or poorer adolescent mental wellbeing, which refers to coefficients β, γ, δ, and ε. I then examine whether there is a rank order in size of the coefficients e.g., whether the association from an hour of social screen time is greater than browsing the internet, playing e-games, or passive video viewing. Then, I run model 4.1 separately for groups of teenagers by sex and parental education to examine the heterogeneity in these relationships.

A concern when estimating the relationship between adolescents' screen time and their wellbeing is reverse causality, i.e., that my coefficient of interest not only estimates the effect of screen time on wellbeing, but also the reverse relationship. For example, adolescents with lower self-esteem may also spend more time on social networking sites. A second concern is unobserved heterogeneity, i.e., that there are unobserved factors (e.g., peer pressure) that may affect both screen behaviour and mental wellbeing. To partially account for these problems, I follow previous studies by including a lagged dependent variable (LDV) (O'Neill et al. 2016; Keele and Kelly 2006).

I use the LDV as a proxy to capture all previous observed or unobserved inputs (e.g. unobserved ability) experienced by the adolescent up to age 11. For example, if an adolescent's parent has strict screen times for their child, who has a good aptitude for school, then the LDV proxies for these observed inputs (parents' screen time rules) and unobservables (aptitude for school) because the inputs by the parents or adolescent are reflected in his/her lagged outcome measure. In addition, I control for extensive observed individual, parental, and demographic characteristics.

LDV, as specified, is of course not without limitations. The model makes strict assumptions such as that the effects of all of the observed and unobservable inputs on skills formation must decline at a constant rate, across age. In Chapter 1 of this thesis, I had explained the assumptions behind this model, and the extensive debate about the using LDVs. Studies have argued that including an LDV in a regression will produce biased coefficient estimates (normally upwards) if the error terms are correlated across time (Achen 2000). On the other hand, Keele and Kelly (2006) demonstrate that if the value of the outcome of interest today is determined by its previous values, an ordinary least squares (OLS) without a lagged outcome will be biased. This is because the OLS assumes that the residual at one point of observation is not correlated with any other residual, which is unlikely since I am examining adolescents' wellbeing across their life. O'Neill et al. (2016) also argue that using LDVs is a good proxy for the effects of the omitted unobserved confounder.

In my specification, I use an LDV to model the process of screen time and wellbeing,

being aware about the validity of the assumptions. I report the estimates with and without the LDV in Appendix Tables A4.8, A4.9, and A4.10 and show that the estimates with and without lagged wellbeing are similar in magnitude. Coefficient estimates on the lagged scores are always positive and statistically significant, indicating that prior mental wellbeing is strongly associated with current wellbeing. After controlling for the lagged scores, sometimes the coefficient estimates are statistically insignificant, especially for the SDQ scores, which shows that there are endogeneity problems that can be accounted for by the lagged scores. For the self-reported estimates, the estimates controlling for lagged wellbeing are slightly larger, which may indicate that those with higher prior wellbeing (and/or unobserved ability) may be engaging in less screen time, but this difference is small.

Finally, given that I examine multiple wellbeing outcomes, any statistically significant result can arise by chance (i.e., false positives). To reduce the chance of false positives, I use more conservative p-values using the Romano-Wolf Multiple Hypothesis Correction after 500 replications, based on Clarke, Romano, and Wolf (2020).

4.5 Findings

4.5.1 Ownership and access to devices

Before examining screen time, we first need to examine access to screens, which is likely differ by parental education. Livingstone et al. (2015), who examined parenting in regarding to media practices across the EU show that less educated parents have a greater generation gap about device use with their children, resulting in worries and more authoritative restrictions in regard to device use. On the other hand, higher income and more educated families use diverse methods to restrict digital device use, such as using parental controls, and trying to promote offline activities for their children to substitute for online activities. Livingstone and Helsper (2007) find that boys, older children, and middle-class children benefit from more and better quality internet access than girls, and younger and working-class children. The authors also find that greater internet use among middle-class children stems from greater home access, which in turn may expose them to greater risk. Parents with lower education (and less resources) may not be able to afford to provide their children with access to devices or the internet and, if they do, they may require the child to share devices with family members.

Figure 4.1 shows children's ownership and access to ICT at ages 7, 11, and 14 (where the information is available), split by parental education. At age 7, slightly more low SES children owned mobile phones and had access to consoles than higher SES children, but this gap was small.[3] At ages 11 and 14, the gap remained small but overall ownership had risen to about 70 – 80%. The largest SES gap concerns whether children had a TV in their bedroom. Two thirds of lower SES children had a TV in their bedroom at age 7 compared to a third of higher SES children. By age 11, the gap had narrowed slightly but remained.

Figure 4.1: Access to screen activities by age

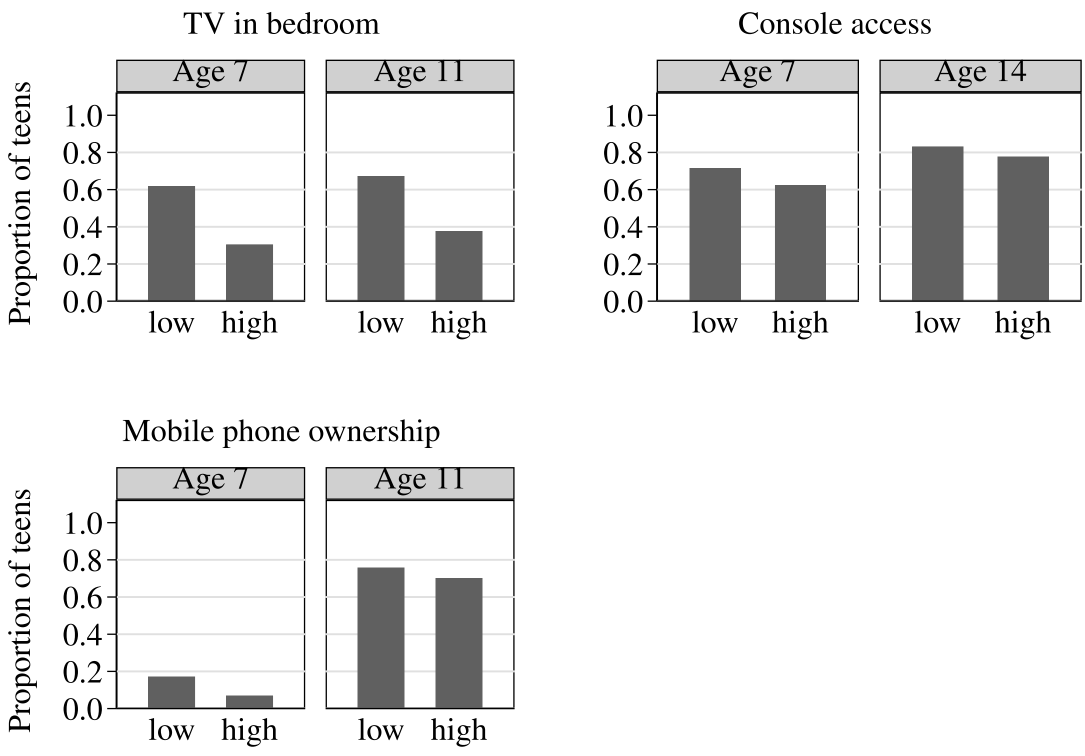


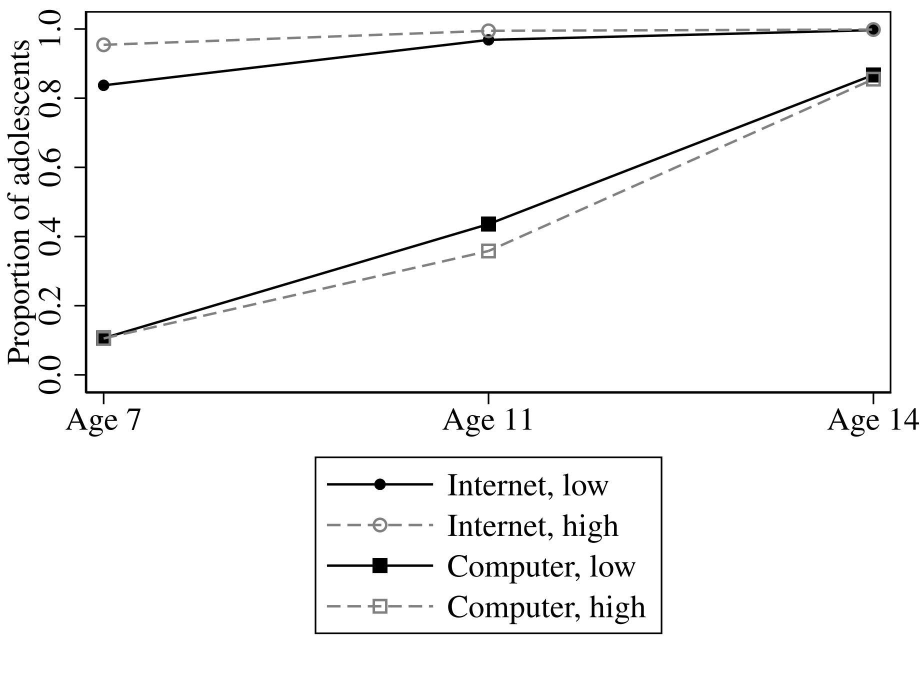
Figure 4.2 shows computer ownership and household internet connection across ages 7 to 14. At age 7, about 80% of low SES children were in households connected to the

[3]Mobile ownership refers to any mobile phones, with or without internet access. At age 11 only, there is information about *access* to mobile phones with an internet connection, and more adolescents from low SES families had access to mobile phones with the internet (30%) than adolescents from higher SES families (20%).

internet while nearly all of the high SES children had internet access. By age 14, this gap had narrowed as nearly all of the adolescents' households were connected to the internet. There are nearly no or only small SES gaps in computer ownership, with computer ownership rising across age for both groups of adolescents. These SES gaps in ownership, access to devices, and the internet, are also similar when comparing across income quintile groups (not shown here). I also find small to no SES gaps for parenting styles in regard to media and TV, as shown in Appendix Table A4.7.

The figures show that for these adolescents, device ownership and internet access increased dramatically between the ages 7 and 14. By age 14, any SES differences in the association between screen time and adolescent wellbeing are unlikely because of device ownership or access. However, I cannot fully discount the fact that low SES families may have had poorer internet connection, and may not have had exclusive ownership of the devices since this is not defined in the data. For example, there may have been "hidden" accessibility problems because adolescents had to share devices amongst household members.

Figure 4.2: Computer ownership and home linked to internet across age, by parental education



Note: "low" denotes parental/partner education below NVQ level 4, and "high" denotes parental/partner education NVQ Level 4 and above.

4.5.2 14-year-olds' screen time and other activities

Table 4.3 reports how the average adolescent spent their time on a weekday and weekend. Column A reports the proportion of adolescents engaged in each activity, column B reports the average hours spent on the activity regardless of participation (includes zero hours) and column C reports the average hours spent on the activity for adolescents engaged in the activity (excludes zero hours). Each column has three sub-columns, which report the estimates for "All" (the average adolescent), the differences between adolescents of low and high parental education, and the differences between girls and boys. For the latter two columns, a negative score indicates that girls (low parent education) engaged less or spent less time on the activity than boys (high parent education).

Column A shows that about 83% and 87% of adolescents engaged in any screen activity on a weekday and weekend respectively. Over half of adolescents engaged in passive video viewing (55% weekday and 64% weekend), followed by social screen time, playing e-games and internet browsing. Girls were more likely than boys to engage in social screen time while boys were more likely than girls to play e-games. Fewer adolescents with low parental education engaged in screen activities compared to those with high parental education, namely internet browsing and watching videos but these differences are small (e.g., 8 percentage points difference in watching videos at the weekend). Adolescents were more likely to engage in educational activities and physical activities at a weekday compared to at the weekend. Slightly more adolescents participate in work/leisure activities at the weekend compared to on a weekday. Girls and adolescents with high parental education were more likely to engage in work/leisure activities alone and in weekend educational activities. Girls and adolescents of low parental education were also less likely to engage in physical activity or exercise.

Column B shows that adolescents spent on average 2.9 hours on any screen activity on a weekday, and 4.1 hours at a weekend. During the weekend, adolescents spent more time on all screen activities and work/leisure, less time on educational activities, and a similar number of hours on physical activity, compared to on a weekday. Boys spent over an hour more on all screen activities compared to girls, while adolescents with low parental education spent 9 minutes more on all screen activities than adolescents with high parental education. Adolescents spent more time on passive video viewing (1 to 2 hours) compared to other screen activities, but there are no significant differences across groups. Boys spent more time playing e-games than girls. Girls and adolescents with high parental education spent more time on social screen time than boys or high SES adolescents.

In column C, conditional on engaging in the activity, adolescents spent more time playing e-games compared to other screen activities, 2 hours 45 minutes on a weekday and 3 hours 20 minutes at the weekend, on average. This was followed by passive video viewing (2 to 3 hours), and social screen time and internet browsing (about 1 to 1 and a half hours). Boys were more likely to play e-games, and spent about 1 hour 45 minutes to 2 hours more on e-games than girls. Boys also exercised for 20 to 45 minutes longer, but spent 27 minutes less on work/leisure, than girls. Most of the differences across parental education in screen time are only evident on a weekday, except for e-games. Adolescents with low parental education spend 30 minutes more playing e-games and 15 minutes more on social screen time and passive video viewing compared to adolescents with high parental education. Adolescents with low parental education also spent less time on sleep and physical exercise, and more time on work/leisure activities alone. There are no differences in hours of sleep across groups.

Table 4.3: Average engagement and hours in activities, by parental education and sex

	(A) Proportion engaged in activity			(B) Average hours if hours≥0			(C) Average hours if hours>0		
	All	Low-High	Girls-Boys	All	Low-High	Girls-Boys	All	Low-High	Girls-Boys
Weekday									
All screen activities	0.83	-0.05***	-0.01	2.94	0.15	-1.06***	3.55	0.37***	-1.23***
Social screen time	0.46	-0.02	0.22***	0.71	0.10	0.34***	1.55	0.28***	0.01
Internet browsing	0.13	-0.03**	-0.03	0.18	-0.03	-0.08**	1.34	0.11	-0.31*
Playing e-games	0.30	-0.03	-0.39***	0.80	0.08	-1.38***	2.71	0.55***	-1.70***
Passive video viewing	0.55	-0.06***	0.07***	1.26	0.01	0.07	2.31	0.26**	-0.15
Sleep	0.98	-0.01**	0.01	8.70	-0.25	-0.15	8.85	-0.13	-0.21
Physical activity or exercise	0.67	-0.07***	-0.02	1.19	-0.15	-0.23***	1.79	-0.03	-0.29***
Work/leisure alone	0.42	-0.07***	0.13***	0.99	0.03	0.42***	2.38	0.42**	0.32
Work/leisure with others	0.70	-0.04	0.02	2.07	-0.02	0.42***	2.97	0.13	0.49***
Educational activities	0.70	-0.02	0.01	4.46	-0.08	-0.06	6.40	0.06	-0.14
Neutral activities	0.94	-0.05***	0.04***	2.50	-0.30***	0.71***	2.66	-0.18	0.66***
Other	0.17	0.08***	-0.01	1.15	0.61***	-0.04	6.73	0.84	0.19
Weekend									
All screen activities	0.87	-0.04***	-0.00	4.14	0.02	-1.24***	4.77	0.24	-1.42***
Social screen time	0.48	0.02	0.26***	0.80	0.15**	0.53***	1.66	0.22	0.22
Internet browsing	0.14	-0.04**	-0.00	0.23	-0.07	-0.11***	1.61	-0.08	-0.72***
Playing e-games	0.35	-0.04	-0.41***	1.17	0.07	-1.85***	3.35	0.55**	-2.11***
Passive video viewing	0.64	-0.08***	0.09***	1.94	-0.13	0.19	3.04	0.19	-0.14
Sleep	0.99	-0.01***	0.00	9.65	-0.23	-0.05	9.78	-0.09	-0.09
Physical activity or exercise	0.53	-0.12***	-0.05**	1.22	-0.09	-0.54***	2.28	0.32**	-0.76***
Work/leisure alone	0.44	-0.09***	0.11***	1.37	-0.07	0.57***	3.13	0.46**	0.49***
Work/leisure with others	0.75	-0.02	0.08***	3.34	0.07	0.71***	4.46	0.23	0.49***
Educational activities	0.29	-0.06***	0.06***	0.59	-0.14**	0.17***	2.04	-0.04	0.14
Neutral activities	0.92	-0.04***	0.05***	2.67	-0.20	0.52***	2.91	-0.08	0.40***
Other	0.17	0.08***	-0.03	1.04	0.63***	-0.14	6.08	1.02	0.15

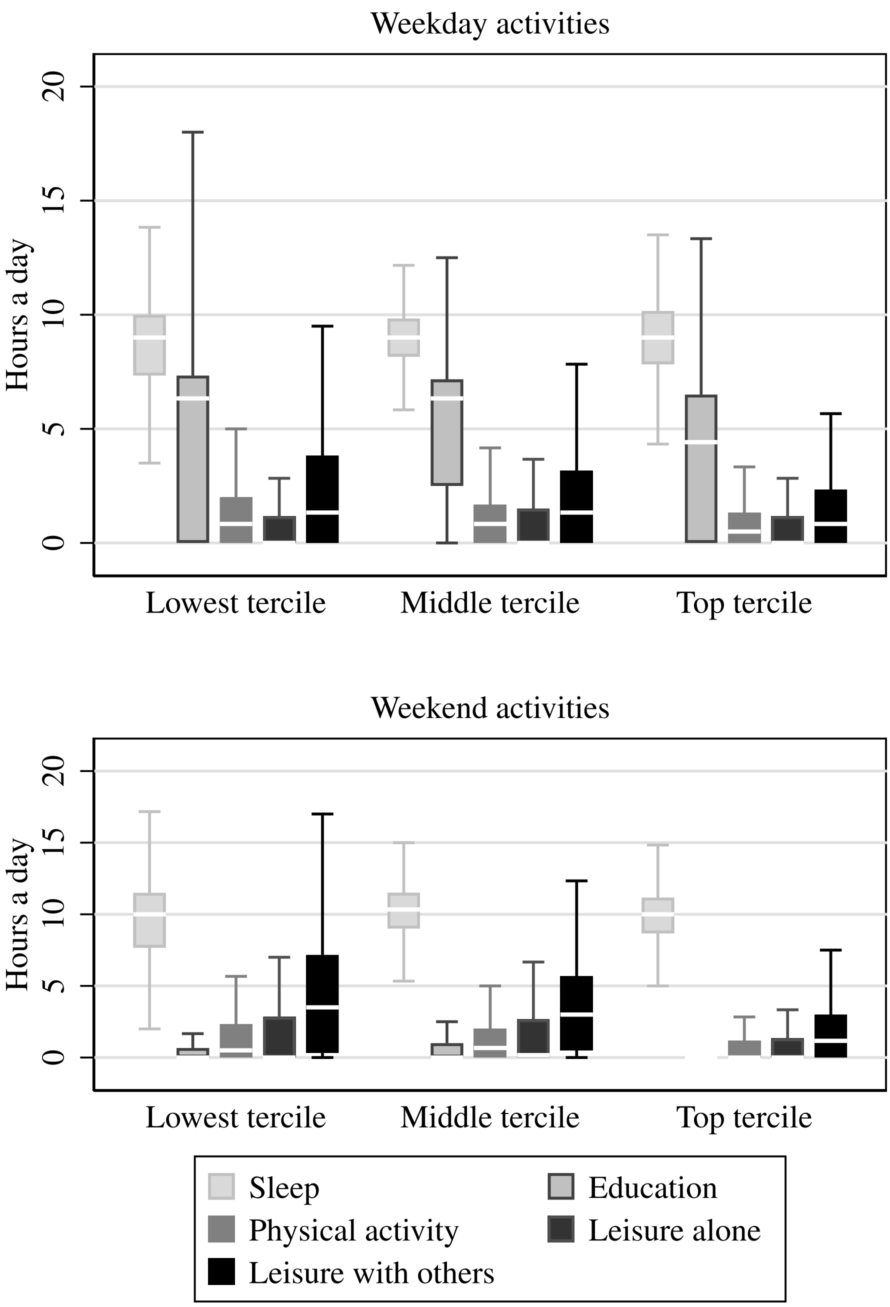
Note: p-values from t-tests of differences in means are indicated by ***<0.01 and **<0.05. Neutral activities refer to activities like personal care and doing nothing. Other are activities not specified by the adolescent. See Appendix Table A4.2 for further detail.

I will now examine the distribution of adolescent time use by hours spent on screen. Figure 4.3 shows boxplots for the distribution of hours spent on each weekend and weekday activity, regardless of engagement in the activity (including zero hours), by terciles of hours of screen time; lowest, middle and top tercile. I split screen hours by terciles as screen hours are distributed differently on a weekday and weekend. The boxes indicate the central range of 50% of the hours spent on the activity. The lower boundary of the box shows the lower quartile hour, the line within the box shows the median hours, and the top boundary of the box shows the upper quartile. The lines (or whiskers) extending from the box indicates the range of the remaining data, outside the central 50%, and the horizontal lines at the end of each whisker show the minimum and maximum hours spent on the activity respectively. Outliers are not reported. In most cases, the hours are positively skewed, and the median hour could be the same as the minimum i.e. zero hours.

On a weekday, adolescents who used screens in the top tercile of hours ($\geq$3.8 hours) spent less time on education, physical activity, and leisure than the others. Since weekdays usually encompass school days, less time spent on educational activities likely means less time spent on homework and school clubs. At the weekend, those in the top tercile of screen hours ($\geq$5 hours) did not spend any time on educational activities, spent less time on physical activities, and notably, much less hours on leisure alone or with others compared to adolescents whose screen time was in the middle or lowest tercile. Overall, there is little difference in the median hours of sleep, and not much difference in the distribution of hours of sleep.

Adolescents who spend an excessive number of hours on screens may be spending less time engaged in face-to-face interactions, social activities, and leisure activities on their own. The overall time spent on physical activities or exercise is generally quite low regardless of the time spent on screens, at an average of 1 hour including activities like travelling via bicycle or walking. This suggests that there were sedentary tendencies among the adolescents in this sample. However, those who used screens in the top tercile of hours spent even lower hours on physical activities compared to those who used screens in the bottom and middle tercile, especially on the weekend.

Figure 4.3: Boxplots of hours in other activities, by screen time



Note: Outliers are not shown here. The range of hours by terciles are as follows: 0 - 1.5 hours, 1.6 - 3.7 hours, and ≥3.8 hours on a weekday. 0-2 hours, 2.3 - 5 hours, and ≥5 hours on a weekend.

4.5.3 Are screen activities bad for adolescent's wellbeing?

Tables 4.4 to Table 4.6 report the regression estimates of the associations between an additional hour of screen activity and adolescent mental wellbeing, controlling for individual and family characteristics, early year social and emotional competencies, survey mode, the respective lagged wellbeing measures, the full time portfolio of activities, and region indicators. All of the tables report estimates for screen time hours on a weekday and at the weekend. All of the coefficient estimates of interest are reported with Romano-Wolf p-values after 500 replications. Since the full time portfolio is considered in this analysis, the tables report the coefficient estimates of β, γ, δ, and ε in model 4.1 as an additional hour of screen activity instead of an hour of sleep.

In Table 4.4 and Table 4.5, more screen time is associated with poorer self-esteem and happiness with the way they look across all types of screen activities. The p-values from the test for equality in coefficient sizes show that the estimates for social screen time and internet browsing are not significantly different from each other, but each are larger than for e-games and passive video viewing. For example, an hour of weekday social screen time is associated with -0.09SD of self-esteem and -0.08SD for internet browsing, while the estimate for passive video viewing and playing e-games are similar, at about -0.03SD. Given that -0.09 is three times the magnitude of having worse wellbeing as a result of having a long-term illness (-0.2SD), the magnitude of the estimates for social screen time and internet browsing is non-trivial.

More time spent on social screen time and internet browsing is associated with lower self-esteem and happiness in all six domains of life. More time playing e-games or passive video viewing during the weekday is only associated with lower happiness with looks (-0.03SD and -0.05SD respectively). All of the estimates are larger in magnitude if the activity is performed on a weekday compared to at the weekend. The consistent associations between screen time (all except e-games) and self-esteem and happiness with looks suggests that these activities may have promoted content that places heavy emphasis on the ideal body image.

Table 4.4: Regression estimates for self-esteem

	Weekday	Weekend
Social screen time	-0.088***	-0.063***
	(0.017)	(0.014)
Internet browsing	-0.078**	-0.063***
	(0.030)	(0.019)
Playing e-games	-0.025	-0.019
	(0.013)	(0.011)
Passive video	-0.029**	-0.011
	(0.011)	(0.010)
Lagged self-esteem	0.269***	0.268***
	(0.021)	(0.019)
Test for equality of coefficients		
social=internet	0.747	0.986
social=e-gaming	0.001	0.006
social=passive video	0.001	0.001
internet=e-gaming	0.080	0.032
internet=passive video	0.111	0.011
e-gaming=passive video	0.799	0.518
Observations	3,143	3,182
R-squared	0.226	0.226

Note: *** p<0.01, ** p<0.05, * p<0.1, Romano-Wolf p-values after 500 replications. All estimates control for individual, demographic, family characteristics, early years personality, survey mode, stratum, full vector of "other" activities such as education, physical activity, work/leisure time with others and alone, and the respective lagged wellbeing scores. Standard errors are reported in parentheses. All estimates are weighted using sampling weights for the whole of UK-level analysis in sweep 6, stratum divided into two for each region; advantaged or disadvantaged, and clustered at the ward level.

Table 4.5: Regression estimates for self-reported happiness in six domains

	Life		Look		Family		Friend		School		School Work	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	-0.077***	-0.035	-0.070***	-0.046***	-0.087***	-0.035	-0.038**	-0.037	-0.050**	-0.036	-0.051***	-0.041*
	(0.016)	(0.018)	(0.015)	(0.015)	(0.017)	(0.017)	(0.015)	(0.019)	(0.017)	(0.017)	(0.018)	(0.017)
Internet browsing	-0.097***	-0.038	-0.065	-0.060**	-0.126**	-0.052	-0.103***	-0.026	-0.089**	-0.012	-0.063	-0.021
	(0.029)	(0.021)	(0.029)	(0.023)	(0.039)	(0.025)	(0.025)	(0.024)	(0.030)	(0.022)	(0.030)	(0.019)
Playing e-games	-0.016	0.009	-0.033**	-0.021	-0.005	-0.001	-0.016	0.003	-0.013	0.001	-0.002	0.003
	(0.013)	(0.011)	(0.012)	(0.011)	(0.013)	(0.010)	(0.015)	(0.012)	(0.014)	(0.013)	(0.013)	(0.010)
Passive video	-0.032	0.010	-0.052***	-0.014	-0.022	0.002	-0.031	0.004	-0.004	0.012	-0.023	-0.003
	(0.015)	(0.011)	(0.013)	(0.012)	(0.013)	(0.010)	(0.015)	(0.011)	(0.014)	(0.013)	(0.014)	(0.011)
Lagged score	0.180***	0.179***	0.201***	0.210***	0.123***	0.144***	0.134***	0.130***	0.106***	0.128***	0.192***	0.194***
	(0.019)	(0.020)	(0.023)	(0.023)	(0.021)	(0.022)	(0.023)	(0.023)	(0.024)	(0.022)	(0.021)	(0.023)
T-test of equality of coefficients												
social=internet	0.233	0.886	0.887	0.606	0.332	0.499	0.0190	0.675	0.222	0.303	0.710	0.361
social=e-gaming	0.00556	0.00901	0.0373	0.137	5.56e-05	0.0429	0.234	0.0404	0.0665	0.0358	0.0132	0.00748
social=passive video	0.0391	0.00967	0.303	0.0587	0.000693	0.0323	0.667	0.0285	0.0254	0.00347	0.141	0.0276
internet=e-gaming	0.00404	0.0220	0.260	0.0697	0.00205	0.0306	0.00117	0.231	0.0111	0.585	0.0521	0.225
internet=passive video	0.0180	0.0155	0.665	0.0431	0.00778	0.0370	0.00702	0.152	0.00955	0.301	0.201	0.371
e-gaming=passive video	0.391	0.887	0.272	0.613	0.319	0.797	0.443	0.910	0.562	0.443	0.235	0.629
Observations	3,143	3,182	3,143	3,182	3,143	3,182	3,143	3,182	3,143	3,182	3,143	3,182
R-squared	0.168	0.148	0.182	0.180	0.104	0.094	0.063	0.063	0.120	0.098	0.130	0.112

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, Romano-wolf p-values after 500 replications. Refer to Table 4.4 above.

Table 4.6: Regression estimates for parent-reported wellbeing

	Total SDQ		Internalising		Externalising		Prosocial	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	0.000	0.015	0.013	0.030*	-0.012	-0.007	-0.047**	-0.033
	(0.012)	(0.010)	(0.014)	(0.012)	(0.012)	(0.011)	(0.018)	(0.017)
Internet browsing	-0.050	-0.007	-0.068**	-0.027	-0.012	0.013	-0.026	-0.072**
	(0.022)	(0.016)	(0.023)	(0.017)	(0.021)	(0.015)	(0.029)	(0.027)
Playing e-games	-0.008	-0.001	-0.011	-0.007	-0.008	-0.002	-0.014	-0.024
	(0.012)	(0.010)	(0.010)	(0.011)	(0.012)	(0.010)	(0.012)	(0.011)
Passive video	-0.005	0.015	-0.019	0.009	0.010	0.015*	0.015	-0.011
	(0.011)	(0.009)	(0.013)	(0.009)	(0.010)	(0.009)	(0.013)	(0.011)
Lagged score	0.613***	0.654***	-0.545***	-0.550***	-0.647***	-0.681***	-0.488***	-0.507***
	(0.028)	(0.021)	(0.022)	(0.022)	(0.026)	(0.021)	(0.023)	(0.023)
T-test of equality of coefficients								
social=internet	0.036	0.197	0.002	0.003	0.984	0.277	0.508	0.246
social=e-gaming	0.578	0.147	0.137	0.008	0.788	0.631	0.094	0.633
social=passive video	0.695	0.941	0.058	0.089	0.151	0.055	0.001	0.218
internet=e-gaming	0.054	0.696	0.015	0.267	0.876	0.408	0.690	0.091
internet=passive video	0.061	0.161	0.047	0.040	0.348	0.873	0.193	0.033
e-gaming=passive video	0.849	0.101	0.597	0.130	0.111	0.115	0.089	0.307
Observations	3,143	3,182	3,143	3,182	3,143	3,182	3,143	3,182
R-squared	0.503	0.523	0.434	0.423	0.501	0.531	0.286	0.298

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, Romano-wolf p-values after 500 replications. Total difficulties, internalising behaviour, and externalising behaviour scales are reverse-coded. All negative estimates indicate worse behavioural problems for all scores. See tables notes in Table 4.4 above.

Table 4.6 reports fewer statistically significant associations between screen time and parent-reported behavioural problems compared to the self-reported scores. More social screen time is associated with poorer prosocial behaviour, but improved internalising behaviour. Since studies have shown that self-esteem plays a strong role in the onset of internalising problems (Harter 1993; Evans, Hawton, and Rodham 2004) and that adolescents low self-esteem often experience internalizing psychopathology (i.e., anxiety, depression) (Ngo, VanderLaan, and Aitken 2020), one would have expected that more screen time is also associated with poorer internalising scores. These differences may indicate that parents (observers) are under-reporting the associated negative wellbeing of their children (Johnston et al. 2014; Hazell et al. 2022), or that these parent-reported measures are capturing different wellbeing issues demonstrated by their child's outward behaviour (e.g., poorer pro-social behaviour) compared to what their child is feeling.

In addition, Table 4.6 shows that an additional hour of internet browsing instead of sleep is associated with worse total behavioural difficulties (-0.05SD), internalising behaviour (-0.07SD), and prosocial behaviour (-0.07SD). The estimates for playing e-games or passive video viewing are either statistically insignificant or small in magnitude. Therefore compared to self-reported estimates, browsing the internet seems to be the 'worse' screen activity instead of social screen time.

4.5.4 Differences by sex and parental education

To examine the variations by sex and parental education, I fit model 4.1 separately for four sub-groups; (1) High parental education, boys (2) High parental education, girls (3) Low parental education, boys (4) Low parental education, girls. All tables for weekday estimates are reported in Appendix Tables A4.15 to Table A4.18. The tables report the coefficient estimates of screen activities by sub-groups, and I use a t-test of seemingly unrelated regressions to test whether the coefficients for each sub-group are equal e.g., if the coefficient for boys, high parental education and girls, high parental education are significantly different using Bonferroni p-values (not reported in the tables).

In line with previous studies, the most salient association is between social screen time and poorer happiness with looks and self-esteem for girls. This re-iterates what has been shown in previous literature, that girls are more vulnerable to social media, arguably from body image problems and early sexualisation. In addition, I find that boys and girls with high parental education fare worse in their happiness in relation to social screen time, compared to adolescents with lower parental education. Girls with high parental education also and have worse internalising behaviour in relation to browsing the internet. In contrast to previous hypothesis in the literature, having high parental education is not a protective factor for girls. While I have ruled out the differences in 'digital divide' in terms of ownership of devices and internet access (as in subsection 4.5.1), we still do not know about content viewed, internet quality, and whether devices are shared amongst less well-off adolescents. Firstly, adolescents with more resources may have better internet quality, more likely to have sole ownership of their devices (and multiple devices), allowing them better access to a wide variety of platforms which are more 'in trend' exposing them not only more frequently to upward comparisons (e.g., Snapchat allows more frequent posts than Facebook in 2015), but also a wider range of risks in terms of harmful content from the internet. This may exacerbate problems with content already seen to be more harmful for girls than boys. Secondly, as discussed in Winstone et al. (2022), adolescents with high parental education may use social media platforms differently to adolescents with lower parental education. It may be that adolescents with greater resources are more able to 'broadcast' and interact with content sharing compared to adolescents who have lower resources. These greater investments in content creation (not captured in time spent on social media), may lead to greater reliance on positive feedback from social networking sites. Lastly, adolescents with higher educated parents are also likely to be friends with other adolescents that have families with resources, which may fuel a competition for upward comparisons through internet platforms (e.g., family holidays abroad, access to branded goods). However, these potential reasons cannot be examined in this study since we do not observe the content on the internet.

As seen in Appendix Table A4.15, more weekday social screen time is associated with lower self-esteem for all sub-groups except for boys from low parental education. However, there are no significant differences in magnitude across the sub-groups. On the weekend, more social screen time is associated with -0.12SD worse self-esteem for girls from high parental education, statistically significant at the 1% level. The coefficient is not different to girls with low parental education, but is significantly different to estimates for boys regardless of education, suggesting that these differences are driven by gender. More time browsing the internet is associated with lower self-esteem by 0.07SD for boys of low parental education, but the estimates are not statistically different across the sub-groups.

For happiness scores, more social screen time is associated with lower happiness for boys and girls with high parental education in the majority of the happiness domains, depending if the activity was on the weekday or weekend. The difference in weekday magnitudes is not statistically different between boys and girls with high parental education. However, there are significant differences in happiness with family and friends between boys of high parental education (-0.1SD and -0.08SD respectively) compared to boys of low parental education (-0.01SD and -0.00SD respectively). Notably, the estimate sizes for boys with low parental education's happiness are near zero, or positive. This indicates that adolescents of higher parental education have lower happiness associated with more weekday social screen time.

For weekend estimates, girls with high parental education have a negative association between social screen time and happiness with life (-0.09SD), looks (-0.10SD), friends (-0.09SD) and school (-0.09SD), but not family. The magnitudes in happiness with looks and school is statistically significantly different to boys regardless of parental education, but not girls with low parental education, indicating that this is driven by gender. There are no statistically significant differences in e-games or passive video viewing with respect to happiness across sub-groups.

As in the baseline regression estimates, it is not social screen time but rather internet browsing that is worse for behavioural scores. An additional hour of weekday social screen time is associated with -0.04SD lower externalising scores for girls with lower parental education, but the magnitude is similar across all sub-groups.

More time browsing the internet is associated with a poorer total behavioural score, and internalising score, for girls with high parental education (-0.13SD and -0.21SD respectively). The magnitude for the former coefficient is only different to girls with low parental education, suggesting a socio-economic difference. Estimates for the latter internalising score is significantly different to all sub-groups, suggesting that internet browsing is associated with worse internalising behaviour for girls with high parental education. Weekend internet browsing is also associated with lower internalising score for boys from high parental education, but is not significantly different to the other sub-groups.

4.5.5 Is the relationship between screen time and wellbeing monotonic?

While more screen time may be associated with poorer mental wellbeing, this relationship may not necessarily be more-is-worse i.e., negative and monotonic. Instead, recall the 'Goldilocks Hypothesis', which posits that there may be a curvilinear relationship. Very low levels of screen time may indicate deprivation, very high levels of screen time may indicate obsessive use of screen time, and there may be a level of screen use inbetween that is 'just right' and even positively associated with mental wellbeing.

To examine these relationships, I re-run my estimates using terciles of the hours spent on each screen activity, using those who do not spend time on screens as the base category. I use terciles of hours spent on each screen activity to ensure similar sample sizes within each tercile because the range of hours differ across screen types and by weekend and weekday. The estimates for self-reported wellbeing are reported in Table 4.7 for the weekday and Table 4.8 for the weekend. Parent-reported wellbeing estimates are in Appendix Tables A4.19 and A4.20. The p-values testing for the equality of coefficients across the terciles are reported at the bottom of the tables. If there is a more-is-worse relationship, I expect to see increasingly larger and negative estimates from the lowest to top tercile of hours. If the relationship is curvilinear, I expect to see larger negative estimates for the lowest and top tercile, compared to the middle tercile, conditional on the estimates being statistically significantly different from each other.

There is an overall negative and monotonic relationship between screen use and *self-reported* wellbeing. The coefficient estimates become progressively larger and more negative from the lowest tercile to the highest tercile hours of screen activity, but are mainly evident for social screen time estimates. There is no evidence of a more-is-worse relationship for parent-reported scores, as the majority of the coefficient estimates are similar in size.

Excessive hours of social screen time, especially during the weekday, are associated with poorer self-reported mental wellbeing. Adolescents who are in the top tercile of hours of weekday social screen time compared to those who do not engage with social screen time are associated with 0.2 to 0.3SD lower self-esteem, and happiness with life, looks and family. Adolescents who spend excessive hours browsing the internet on the weekday also have lower happiness with their friends and family (-0.4 and -0.3SD respectively) compared to those who do not use the internet. However, excessive hours spent playing e-games or passive video viewing are not associated with poorer self-reported wellbeing. Excessive screen use is also not adversely associated with adolescents' wellbeing as reported by their parents (see Appendix Tables A4.19 and A4.20).

I find some indication of the 'Goldilocks Hypothesis', but only for few estimates, i.e., weekend passive video viewing. In both Table 4.8 and Appendix Table A4.20, adolescents who spend moderate hours on passive video viewing at the weekend compared to adolescents who do not watch videos are associated with greater self-esteem, happiness with school, and better parent-reported externalising behaviour. The coefficient estimate sizes are mainly different between the lowest and middle tercile hours. In Appendix Table A4.20, those who spend the middle tercile of social screen time are associated with better total behavioural and internalising scores compared to those who do not use social screen time. However, the magnitude of the estimates across terciles are not statistically significantly different. While my estimates provide some evidence for this hypothesis, I am unable to specify the exact number of hours when passive video viewing change from having beneficial to harmful associations with mental wellbeing.

Table 4.7: Tercile hours of screen time on self-reported wellbeing, weekday

Self-reported	Self-esteem	Life	Look	Family	Friend	School	School Work
Social screen time							
Lowest tercile	0.020	0.076	-0.013	0.097*	0.105*	0.074	0.022
	(0.055)	(0.050)	(0.053)	(0.053)	(0.055)	(0.050)	(0.058)
Middle tercile	-0.030	-0.018	-0.080	-0.069	-0.019	0.064	-0.088
	(0.057)	(0.058)	(0.065)	(0.062)	(0.068)	(0.059)	(0.062)
Top tercile	-0.291***	-0.261***	-0.192*	-0.270***	-0.065	-0.114	-0.133
	(0.064)	(0.066)	(0.064)	(0.075)	(0.063)	(0.073)	(0.076)
Internet							
Lowest tercile	-0.050	-0.157	-0.052	-0.073	-0.181	-0.022	0.011
	(0.116)	(0.121)	(0.114)	(0.113)	(0.122)	(0.108)	(0.106)
Middle tercile	-0.005	-0.195	-0.014	-0.080	-0.020	-0.091	0.012
	(0.094)	(0.124)	(0.085)	(0.147)	(0.101)	(0.135)	(0.115)
Top tercile	-0.148	-0.234	-0.221	-0.377**	-0.300**	-0.218	-0.285
	(0.103)	(0.099)	(0.092)	(0.112)	(0.090)	(0.103)	(0.112)
Playing e-games							
Lowest tercile	-0.017	0.011	-0.054	-0.022	-0.035	0.071	0.065
	(0.069)	(0.069)	(0.062)	(0.069)	(0.083)	(0.069)	(0.079)
Middle tercile	-0.056	0.042	-0.027	0.103	0.041	0.073	0.092
	(0.061)	(0.068)	(0.059)	(0.065)	(0.069)	(0.073)	(0.071)
Top tercile	-0.094	-0.061	-0.179	-0.015	-0.072	-0.123*	-0.037
	(0.080)	(0.078)	(0.071)	(0.078)	(0.082)	(0.073)	(0.081)
Passive video							
Lowest tercile	0.075	0.050	0.097	0.025	0.099	0.136	0.171**
	(0.053)	(0.050)	(0.052)	(0.060)	(0.068)	(0.048)	(0.053)
Middle tercile	0.073	0.031	-0.001	0.022	0.003	0.102	0.113
	(0.053)	(0.051)	(0.054)	(0.058)	(0.059)	(0.056)	(0.057)
Top tercile	-0.087	-0.105	-0.165	-0.051	-0.087	0.014	-0.067
	(0.056)	(0.062)	(0.060)	(0.058)	(0.069)	(0.061)	(0.065)
Observations	3143	3143	3143	3143	3143	3143	3143
R^2	0.224	0.170	0.180	0.105	0.066	0.124	0.137
p-values for equality of coefficients							
social low=mid	0.452	0.157	0.337	0.009	0.079	0.873	0.104
social mid=high	0.000	0.003	0.170	0.023	0.548	0.029	0.593
social low=high	0.000	0.000	0.020	0.000	0.018	0.012	0.059
internet low=mid	0.751	0.815	0.778	0.971	0.282	0.672	0.994
internet mid=high	0.306	0.809	0.100	0.107	0.038	0.418	0.063
internet low=high	0.530	0.616	0.248	0.054	0.402	0.183	0.055
e-games low=mid	0.653	0.713	0.714	0.124	0.375	0.982	0.785
e-games mid=high	0.645	0.232	0.066	0.212	0.206	0.034	0.133
e-games low=high	0.402	0.409	0.149	0.942	0.701	0.028	0.325
video low=mid	0.982	0.758	0.098	0.959	0.189	0.561	0.336
video mid=high	0.009	0.030	0.009	0.273	0.173	0.157	0.006
video low=high	0.006	0.020	0.000	0.202	0.014	0.062	0.001

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard error in parentheses. Estimates control for same control variables as in baseline estimates. Romano-wolf p-values reported for statistical significance reported.

Table 4.8: Tercile hours of screen time on self-reported wellbeing, weekend

Self-reported	Self-esteem	Life	Look	Family	Friend	School	School Work
Social screen time							
Lowest tercile	0.052	0.060	0.102	0.069	0.091	0.019	-0.045
	(0.053)	(0.057)	(0.053)	(0.055)	(0.053)	(0.051)	(0.061)
Middle tercile	-0.101	-0.029	-0.055	0.034	0.038	-0.057	-0.164
	(0.058)	(0.061)	(0.061)	(0.063)	(0.076)	(0.069)	(0.066)
Top tercile	-0.188**	-0.075	-0.141	-0.092	-0.091	-0.106	-0.194*
	(0.060)	(0.070)	(0.067)	(0.066)	(0.076)	(0.071)	(0.069)
Internet							
Lowest tercile	-0.022	-0.034	-0.008	0.016	-0.052	0.125	0.047
	(0.096)	(0.114)	(0.099)	(0.110)	(0.118)	(0.086)	(0.095)
Middle tercile	-0.064	-0.145	-0.058	0.029	0.056	0.110	0.172
	(0.099)	(0.096)	(0.106)	(0.087)	(0.094)	(0.092)	(0.087)
Top tercile	-0.196	-0.063	-0.217	-0.169	-0.028	0.061	-0.021
	(0.100)	(0.087)	(0.100)	(0.098)	(0.083)	(0.084)	(0.094)
Playing e-games							
Lowest tercile	0.125	0.111	-0.025	0.147	0.088	0.112	0.078
	(0.066)	(0.059)	(0.059)	(0.058)	(0.062)	(0.055)	(0.062)
Middle tercile	0.081	0.107	0.036	0.117	0.183**	0.150	0.126
	(0.059)	(0.063)	(0.060)	(0.068)	(0.061)	(0.062)	(0.055)
Top tercile	-0.081	0.093	-0.157	0.040	0.048	0.079	0.060
	(0.083)	(0.080)	(0.087)	(0.077)	(0.086)	(0.087)	(0.079)
Passive video							
Lowest tercile	0.002	-0.045	-0.038	-0.040	0.044	0.088	0.137
	(0.054)	(0.056)	(0.054)	(0.064)	(0.062)	(0.065)	(0.058)
Middle tercile	0.136*	0.115	0.089	0.102	0.122	0.153*	0.133
	(0.048)	(0.053)	(0.057)	(0.056)	(0.054)	(0.056)	(0.056)
Top tercile	-0.013	0.079	-0.043	0.020	0.067	0.137	0.035
	(0.057)	(0.061)	(0.058)	(0.059)	(0.058)	(0.069)	(0.064)
Observations	3182	3182	3182	3182	3182	3182	3182
R^2	0.231	0.151	0.184	0.099	0.068	0.105	0.122
p-values for equality of coefficients							
social low=mid	0.011	0.180	0.020	0.612	0.458	0.288	0.090
social mid=high	0.191	0.561	0.223	0.142	0.146	0.580	0.687
social low=high	0.001	0.071	0.001	0.046	0.013	0.121	0.050
internet low=mid	0.742	0.421	0.736	0.920	0.434	0.905	0.301
internet mid=high	0.366	0.516	0.246	0.102	0.477	0.680	0.101
internet low=high	0.226	0.850	0.156	0.216	0.865	0.580	0.616
e-games low=mid	0.047	0.853	0.023	0.331	0.094	0.361	0.420
e-games mid=high	0.057	0.799	0.027	0.359	0.094	0.439	0.364
e-games low=high	0.028	0.842	0.172	0.231	0.665	0.707	0.847
video low=mid	0.017	0.004	0.032	0.026	0.198	0.311	0.949
video mid=high	0.008	0.548	0.027	0.176	0.361	0.816	0.105
video low=high	0.812	0.053	0.925	0.378	0.738	0.497	0.098

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard error in parentheses. Romano-Wolf p-values after 500 replications for main coefficient estimates. Estimates control for same control variables as in baseline estimates.

4.5.6 Robustness checks

Not all of the adolescents reported both a weekday and weekend time diary. While the majority of the sample reported both days, some reported only one of the days i.e., a weekend or weekday. In the case that there were unobserved differences between adolescents who reported both time diary days and those who did not, I re-run my estimates using a constrained sample of adolescents who *only* reported both days (n=2,889). As reported in Appendix Table A4.21 and Table A4.22, my estimates are robust to the choice of sample, yielding similar estimate sizes and statistical significance. The main differences are that the weakly significant (at the 10% level) estimates in the original baseline regressions become statistically insignificant using the more selected sample, possibly due to the smaller sample size.

4.6 Discussion and concluding remarks

The goal of this study was to examine four research questions: 1) Which screen activity is worse for adolescent wellbeing? 2) Do the relationships vary depending on the types of wellbeing measures? 3) How do these relationships vary by both gender and parental education? 4) Does excessive screen time equate to worse mental wellbeing? The main complications stem from not defining screen activities well enough, the difference in observers that report adolescent wellbeing, and the variations in the relationships between screen use and wellbeing by parental education, sex, and hours spent on screen.

4.6.1 Summary and discussion

Using time diaries of 14-year-old UK adolescents, I find that while adolescents are more likely to engage in passive video viewing compared to other screen activities, adolescents spend most time playing e-games, when engaged in it, followed by passive video viewing, social screen time, and internet browsing. Adolescents who spend more than 3.8 hours on screen time on a weekday and more than 5 hours at a weekend are less likely to spend time on physical activity, educational activities, leisure alone or leisure with others. There is a strong division in screen time by sex; girls spend more time on social screen time while boys play more e-games. Adolescents with low parental education spend more hours on screen activities, but have similar rates of engagement in screen activities compared to adolescents with high parental education. Within this sample, there seems to be little digital divide in terms of computer ownership and internet access by age 14, and few differences in parenting styles by parental education.

To answer the first research question, my estimates show that more time spent on any screen activity is adversely associated with the adolescents' views on themselves, such as self-esteem and happiness with looks. In particular, coefficient estimates from social screen time are the largest compared to the other types of screen activities, suggesting simply in this set of screen activities analysed, social screen time is the 'worst' form of activity, in line with previous studies showing a higher risk of social media being associated with poorer body image and greater risk of self-harm among adolescents (Mcdool et al. 2020; Banthorpe et al. 2020; Booker, Kelly, and Sacker 2018; McNamee, Mendolia, and Yerokhin 2021). The smaller estimates for e-games are in line with the few existing studies that find that video games are unrelated to depression (Bickham, Hswen, and Rich 2015; Kandola et al. 2022), only have small positive associations with behavioural problems (Sanders et al. 2019), and do not promote aggressive behaviour (Przybylski and Weinstein 2019). The smaller estimates for passive video viewing are at odds with Nieto and Suhrcke (2021) who found that more time spent watching TV increases mental health problems for adolescents aged 10 to 15 in the UK but in line with Kandola et al. (2022). This difference might be because Nieto and Suhrcke (2021) exclusively examined television viewing between 2008 and 2012, when other forms of media may not have been as popular; there has been a rise in the popularity of YouTube compared to TV since 2015 (Ofcom 2015) and the broadband speed rose from an average of 15mbps to over 30mbps between 2012 and 2015 (Mcdool et al. 2020).

Second, I find that the types of wellbeing, as well as who reports wellbeing matters for these relationships. Screen time is most strongly associated with Self-reports of wellbeing showed greater associations with social screen time compared to parent-reported scores. Instead, more hours spent browsing the internet and playing e-games are associated with poorer internalising behaviour for adolescents with higher parental education. While we cannot be certain, the disagreement between parent-adolescent reports may suggest that parents and adolescents are reporting two different measures of wellbeing, where parents may be reporting more outward behavioural responses to certain activities (Rescorla et al. 2013). For example, parents may view playing e-games as problematic behaviour, or are observing persistent mood and conduct problems when their children are playing e-games. In contrast, adolescents who spend more time on social screen activities may have lower self-esteem, but may not portray these behavioural visual cues. It may also be that at age 14, parent reports of adolecsents' wellbeing become less similar as adolescents become more self-aware, and also that observers may be more likely to under-report adolescents' mental health as the adolescent gets older (Johnston et al. 2014).

Third, the harmful associations between social screen time and mental wellbeing are worse for girls than boys, as found in previous studies using the MCS (Banthorpe et al. 2020; Kelly et al. 2019) and studies in the UK (McNamee, Mendolia, and Yerokhin 2021; Mcdool et al. 2020). This re-iterates what has been shown in previous literature, that girls are more vulnerable to social media, arguably from body image problems and early sexualisation. Moreover, I find that high parental education is not a protective factor for girls, as boys and girls with high parental education fare worse in their happiness in relation to social screen time, compared to adolescents with lower parental education. This is in sharp contrast to the majority of previous literature. This might occur because of several reasons related to greater resources afforded by adolescents with higher parental education. One, adolescents with higher parental education may afford a wider access of multiple devices and on multiple platforms, despite my analysis showing little differences in digital divide and parenting styles. Certain types of platforms allows different levels of interaction with the platform (e.g., Snapchat allows more frequent posts than Facebook in 2015). Second, adolescents of differing parental education may interact with platforms differently i.e., content creator or viewer on YouTube. Third, adolescents with more resources may have greater upward social comparisons with their peers of similar status. However, none of these reasons can be uncovered in this current analysis, especially since content on screens are not observed.

Lastly, I find that the majority of the relationships between screen use and self-reported mental wellbeing are negative and monotonic, lending support to the more-is-worse hypothesis. Excessive hours of social screen time and internet browsing are detrimental to self-reported wellbeing, but not for playing e-games, passive video viewing, or for parent-reported scores. I find that the relationship between weekend *passive video viewing* and mental wellbeing lends some small support to the 'Goldilocks Hypothesis' where moderate levels of watching videos may be beneficial for wellbeing compared to those who do not watch videos. However, this may likely only hold for activities that are 'normalised' as a day-to-day activity, since weekend passive video viewing is the screen activity that most adolescents engage in.

4.6.2 Conclusions

The Covid-19 pandemic has shown that screen use will continue rising, and there will be continued research and societal interest in how screen use is associated with young people's wellbeing. My study shows that screen time relates to adolescent wellbeing differently depending on how screen time is defined, how wellbeing is measured, and for different groups of teenagers. Being specific helps create more defined policy measures that implicate adolescent mental wellbeing. For example in 2021, China banned children and teenagers from online gaming on school days, and limited their time spent on this to one hour a day at the weekend and in holiday evenings. If playing games is used by families of lower socio-economic backgrounds as a more convenient and accessible way to socialise than doing a paid activity such as going to the movies, then restricting gaming time simply reduces these families' options for leisure. Restricting one activity may not necessarily translate into spending more time on productive activities.

A consistent finding is that social screen time is poorly associated with adolescents' self-image, especially for girls with high parental education. This suggests the importance of the role of parents/guardians and teachers in moderating social media use especially among potentially more vulnerable groups of adolescents. A policy recommendation would be to integrate screen use and mental health awareness into the Personal, Social, Health and Economic education curriculum. Letters from schools could help signpost parents/guardians to third party software to help monitor and moderate screen use (e.g., teaching parents how to use parental controls).

There are several limitations in this paper. Firstly, this analysis uses a cohort study about screen use in 2015, which is not generalisable to all UK adolescents and examines screen use nearly a decade ago, which had different implications to our technological use today. In addition, the time diaries were only issued and returned by a sub-sample of the MCS study, leading to further missingness. The main contribution of this study is conceptualising the types of screen time in more granular detail compared to other studies using rich historical information in the longitudinal data, of which findings are mostly relevant for a cohort of White and relatively advantaged girls. The other limitations are that the MCS did not collect data about media content, nor about secondary activities. Therefore, I cannot discern whether, for example, internet browsing is harmful for wellbeing because the internet contains forums that promote harmful content written by someone else. Not observing secondary data means that I also miss examining adolescents' multi-tasking with screen activities, e.g., walking and texting on the phone, which may indicate addictive-behaviour.

There is extensive scope for future studies to study the types of content viewed on screens, as well as habits related to screen use such as multi-tasking, and their relationships with adolescents' mental wellbeing. More research is also required to understand which wellbeing scores should be analysed with respect to adolescent screen use, especially at the ages when adolescents become more independent and autonomous from their parents. Lastly, it is unclear as to why adolescents with higher parental education may fare worse than their peers with lower parental education, and future studies should consider how adolescents of different socio-economic backgrounds use social screen time (e.g., promote or browse content), and whether there are variations in types of platforms used, especially when internet access and screen use are becoming ever more prevalent in adolescents' lives today.

4.7 Appendix A

4.7.1 Descriptive statistics and definitions

Table A4.1: Characteristics of those with matched TUD information, compared to those who were unmatched

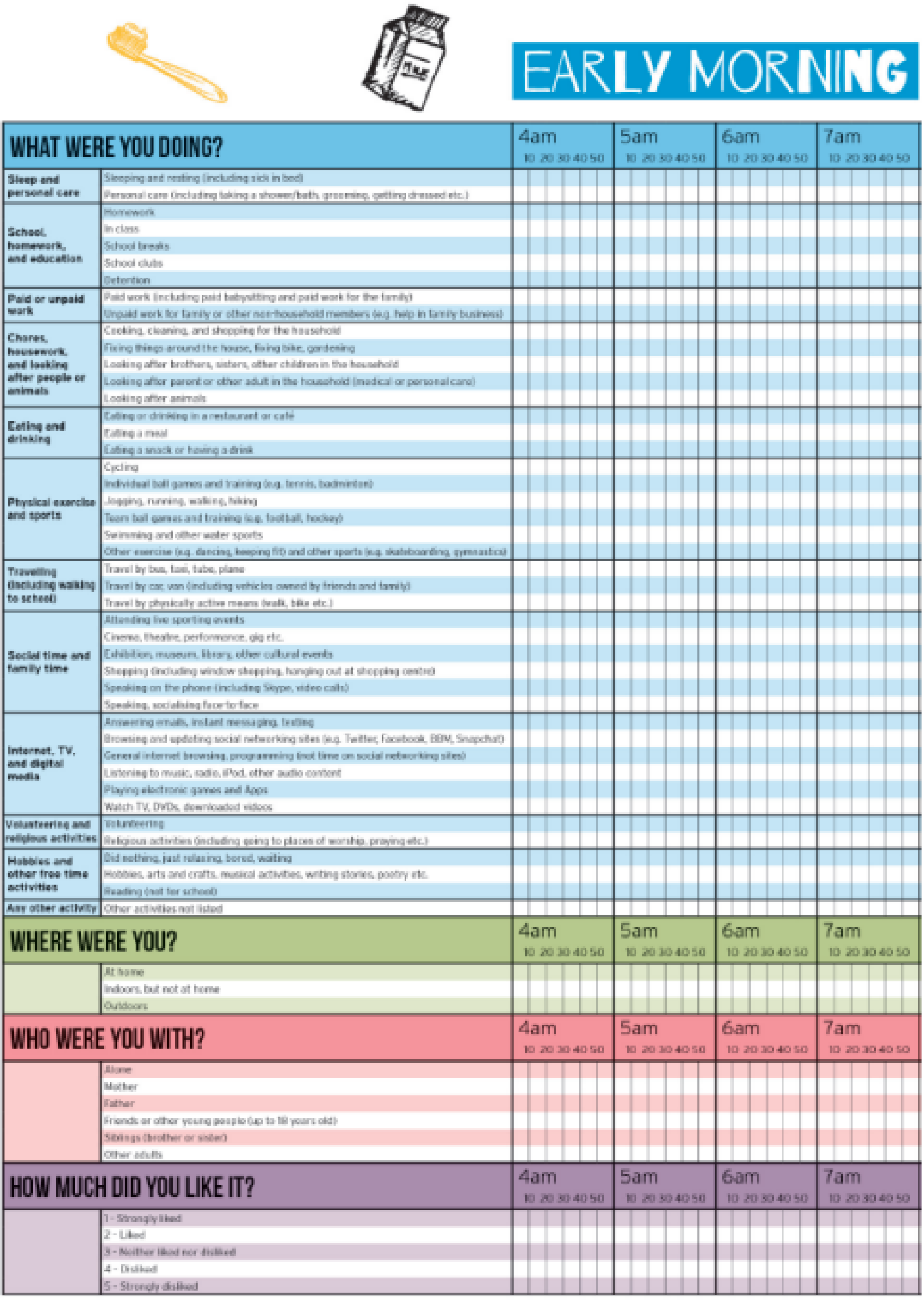
Characteristics	Matched (%)	Unmatched (%)	Matched, weighted (%)	Unmatched, weighted (%)
Age 13 years old	26	24	26	23
Age 14 years old	73	75	73	75
Age 15 years old	1	1	1	2
Female	55	47	53	46
Male	45	53	47	54
White	83	73	83	75
Mixed	4	5	5	6
Indian	3	3	2	2
Pakistani and Bangladeshi	6	8	4	6
Black or Black British	2	4	3	4
Other ethnicity	2	3	2	3
Refused/DK/N/A ethnicity	0	4	1	4
England - Advantaged	29	28	48	43
England - Disadvantaged	21	27	26	34
England - Ethnic	11	15	6	8
Wales - Advantaged	5	4	3	2
Wales - Disadvantaged	10	9	3	2
Scotland - Advantaged	8	4	6	4
Scotland - Disadvantaged	5	5	4	3
Northern Ireland - Advantaged	5	3	2	2
Northern Ireland - Disadvantaged	5	5	2	2
Raw observations	4,640	5,776	4,640	5,776

Table A4.2: Categorised activities from the 44 disaggregated activities in the MCS

Grouped activities	**2nd-level coded activites**
Sleep	Sleeping and resting (including sick in bed)
Education related	Homework
	In class
	School breaks
	School clubs
Physical exercise and sports	Cycling
	Individual ball games and training (e.g., tennis, badminton)
	Jogging, running, walking, hiking
	Team ball games and training (e.g., basketball, football)
	Swimming and other water sports
	Travelling by bicycle/walk
Work/leisure alone	Hobbies, arts and crafts, musical activities, writing stories, poetry etc
	Reading (not for school)
	Volunteering
	Religious activities (incl. going to places of worship, praying etc)
	Paid work (incl. babysitting and paid work for the family)
	Unpaid work for family or other non-household
	Cooking, cleaning and shopping for the household
	Fixing things around the house, fixing bike, gardening
	Looking after brothers, sisters, other children in the household
	Looking after parent or other adult in the household
	Looking after animals
	Eating or drinking in a restaurant or café
	Eating a meal
	Eating a snack or having a drink
	Attending live sporting events
	Cinema, theatre, performance, gig etc
	Exhibition, museum, library, other cultural events
	Shopping (incl. window shopping, hanging out at shopping centre)
	Listening to music, radio, iPod, other audio content
Work/leisure with others	As defined above, but activity performed with others
	Speaking, Socialising face-to-face
Neutral activities	Personal care (including taking a shower, grooming, getting dressed etc)
	Did nothing, just relaxing, bored, waiting
	Detention
	Eating and drinking alone
	Travelling using vehicle
Other	Activity not listed/missing activities

Note: Very few adolescents were doing any paid or unpaid work (2 minutes total average time, including those who did not work, for paid or unpaid work respectively). A further breakdown of minutes spent in each of these 44 activities can be seen in Chatzitherochari et al. (2015).

Figure A4.1: Example of entering activities into the paper mode diary



EARLY MORNING

WHAT WERE YOU DOING?		4am 10 20 30 40 50	5am 10 20 30 40 50	6am 10 20 30 40 50	7am 10 20 30 40 50
Sleep and personal care	Sleeping and resting (including sick in bed)				
	Personal care (including taking a shower/bath, grooming, getting dressed etc.)				
School, homework, and education	Homework				
	In class				
	School breaks				
	School clubs				
	Detention				
Paid or unpaid work	Paid work (including paid babysitting and paid work for the family)				
	Unpaid work for family or other non-household members (e.g. help in family business)				
Chores, housework, and looking after people or animals	Cooking, cleaning, and shopping for the household				
	Fixing things around the house, fixing bike, gardening				
	Looking after brothers, sisters, other children in the household				
	Looking after parent or other adult in the household (medical or personal care)				
	Looking after animals				
Eating and drinking	Eating or drinking in a restaurant or café				
	Eating a meal				
	Eating a snack or having a drink				
Physical exercise and sports	Cycling				
	Individual ball games and training (e.g. tennis, badminton)				
	Jogging, running, walking, hiking				
	Team ball games and training (e.g. football, hockey)				
	Swimming and other water sports				
	Other exercise (e.g. dancing, keeping fit) and other sports (e.g. skateboarding, gymnastics)				
Travelling (including walking to school)	Travel by bus, taxi, tube, plane				
	Travel by car, van (including vehicles owned by friends and family)				
	Travel by physically active means (walk, bike etc.)				
Social time and family time	Attending live sporting events				
	Cinema, theatre, performance, gig etc.				
	Exhibition, museum, library, other cultural events				
	Shopping (including window shopping, hanging out at shopping centre)				
	Speaking on the phone (including Skype, video calls)				
	Speaking, socialising face-to-face				
Internet, TV, and digital media	Answering emails, instant messaging, texting				
	Browsing and updating social networking sites (e.g. Twitter, Facebook, BBM, Snapchat)				
	General internet browsing, programming (not time on social networking sites)				
	Listening to music, radio, iPod, other audio content				
	Playing electronic games and Apps				
	Watch TV, DVDs, downloaded videos				
Volunteering and religious activities	Volunteering				
	Religious activities (including going to places of worship, praying etc.)				
Hobbies and other free time activities	Did nothing, just relaxing, bored, waiting				
	Hobbies, arts and crafts, musical activities, writing stories, poetry etc.				
	Reading (not for school)				
Any other activity	Other activities not listed				

WHERE WERE YOU?		4am 10 20 30 40 50	5am 10 20 30 40 50	6am 10 20 30 40 50	7am 10 20 30 40 50
	At home				
	Indoors, but not at home				
	Outdoors				

WHO WERE YOU WITH?		4am 10 20 30 40 50	5am 10 20 30 40 50	6am 10 20 30 40 50	7am 10 20 30 40 50
	Alone				
	Mother				
	Father				
	Friends or other young people (up to 18 years old)				
	Siblings (brother or sister)				
	Other adults				

HOW MUCH DID YOU LIKE IT?		4am 10 20 30 40 50	5am 10 20 30 40 50	6am 10 20 30 40 50	7am 10 20 30 40 50
	1 - Strongly liked				
	2 - Liked				
	3 - Neither liked nor disliked				
	4 - Disliked				
	5 - Strongly disliked				

Figure A4.2: Example of entering activities into the web mode diary

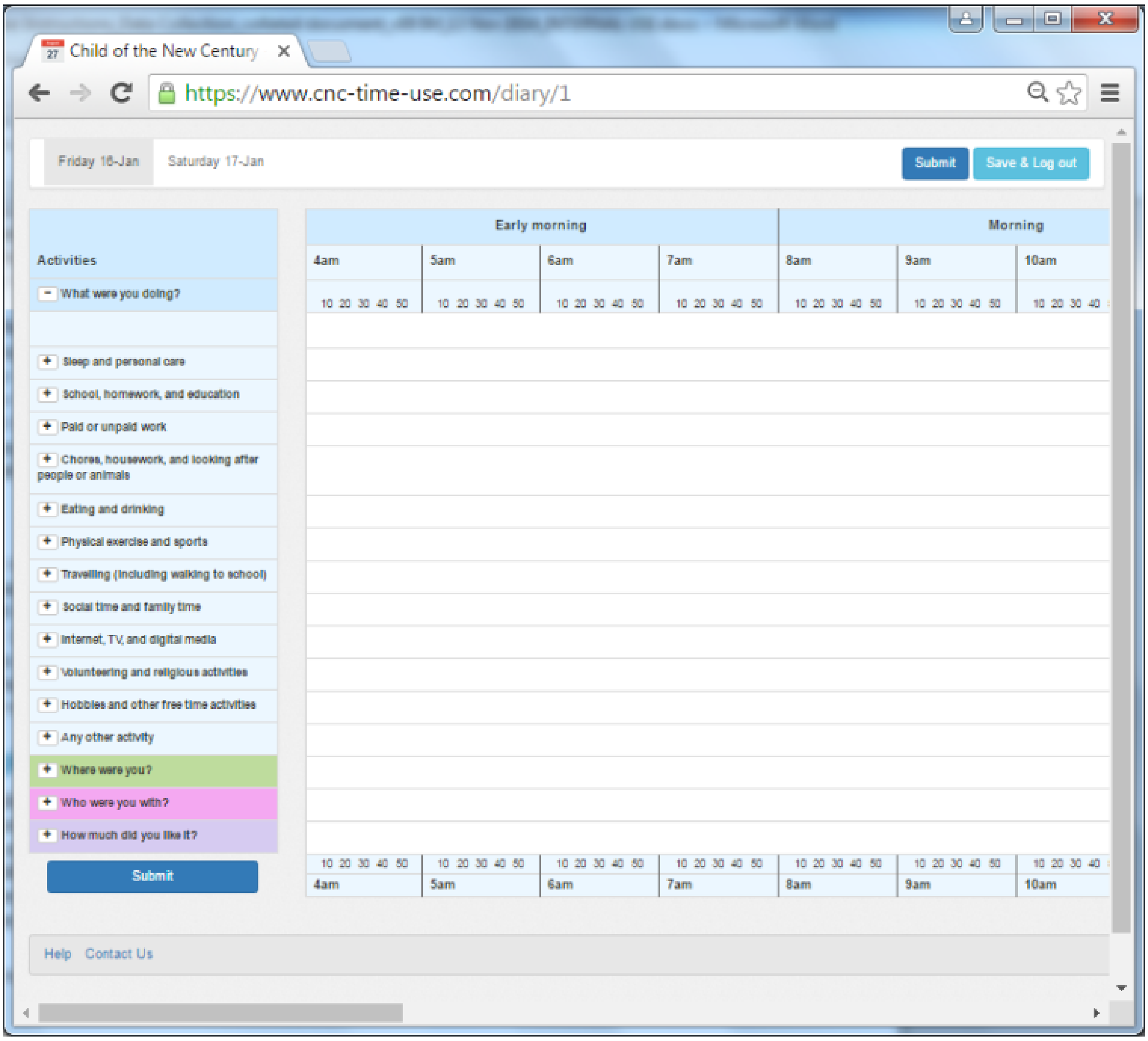


Figure A4.3: Example of entering activities into the app mode diary

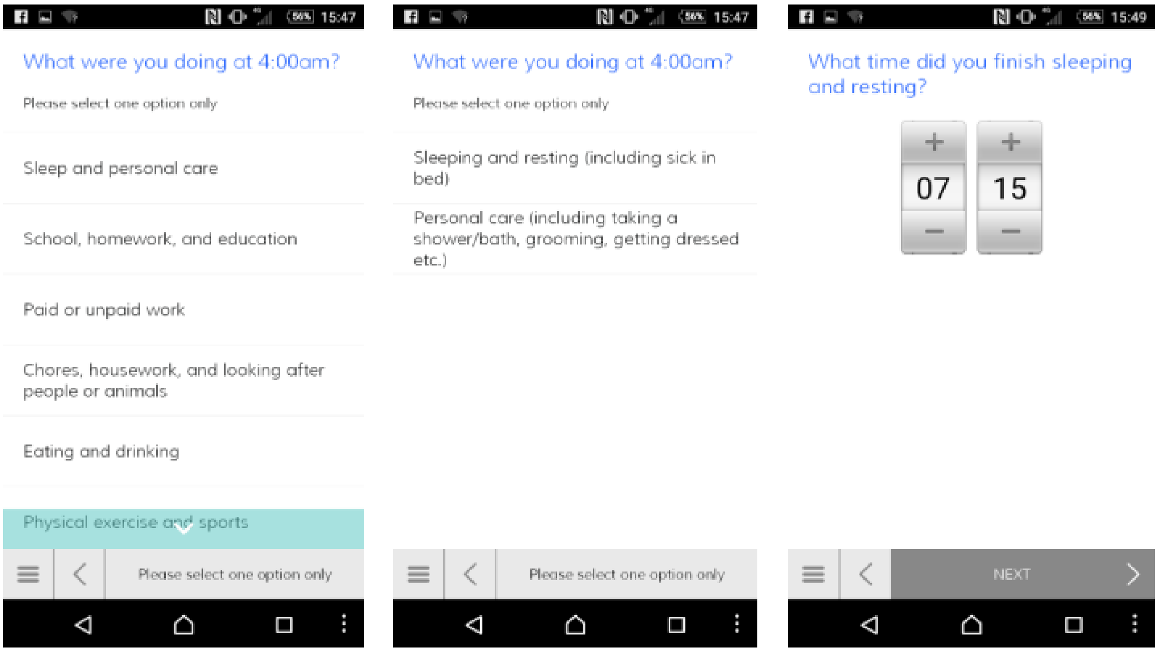


Figure A4.4: Example of format of activities for each adolescent in harmonized file

Time	Activity
……. – 08:50	Breakfast
08:50 – 09:00	Travel to school
09:00 – 09:10	Travel to school
09:10 – 09:20	Travel to school
09:20 – 09:30	Classroom
……. – …….	Classroom
……. – 12:30	Classroom

Table A4.3: List of items for wellbeing scores

Parent-reported Strengths and Difficulties Questions (SDQ)	
(Internalising) Emotional problems	Has many worries, often seems worried
	Has many fears, easily scared
	Complains of headaches/stomach-aches/sickness
	Often unhappy, downhearted, tearful
	Nervous or clingy in new situations
(Internalising) Peer problems	Rather solitary, plays alone
	Has at least one good friend
	Gets on better with adults
	Picked on or bullied by other children
	Generally liked by other children
Prosocial behaviour	Considerate of other people's feelings
	Shares readily with other children
	Often volunteers to help others
	Helpful if someone is hurt, upset, unwell
	Kind to younger children
(Externalising) Hyperactivity/Inattentiveness	Restless, overactive and cannot stay still
	Constantly fidgeting and squirming
	Thinks things out before acting
	Sees tasks through to the end
	Easily distracted
(Externalising) Conduct problems	Often has temper tantrums
	Generally obedient
	Fights with or bullies other children
	Often lies or cheats
	Steals from home, school, elsewhere
Rosenberg self-esteem scale (1="Strongly disagree", 4="Strongly agree")	
	On the whole, I am satisfied with myself
	I feel that I have a number of good qualities
	I am able to do things as well as most people
	I am a person of value
	I feel good about myself
Happiness with ... (1="Not at all happy", 7="Very happy")	
	Your school work
	The way you look
	Your family
	Your friends
	The school you go to
	Your life as a whole

Note: Emotional and peer problems refer to internal problematic behaviours, while hyperactivity/inattentiveness and peer problems refer to external problematic behaviours. The total difficulties score is the sum of internal and external problematic behaviours, where a higher score indicates more problematic behaviours. For prosocial behaviour, a higher score indicates better behaviour.

Table A4.4: Carey Infant's Temperament Scale, at 9 months old

Temperament score	Items
Mood	α: 0.431
	Happy sounds during nappy changing etc
	Pleasant first arriving in unfamiliar places
	Pleasant during hair brushing etc
	Content during interruptions of feeding
	Pleasant or calm with minor injuries
Approach or withdrawal	α: 0.569
	Objects to bathing - different place/person
	Wary of strangers after 15 minutes
	Shy on first meeting another child
Adaptability	α: 0.248
	Fretful in a new place or situation
	Bothered at first by different sleeping place
	Milk feeds at about the same time
Regularity	α: 0.667
	Sleepy at about the same time each evening
	Naps about the same length
	Solid food at about the same time

Note: A higher score indicates worse temperament

Table A4.5: Cross-tabulation of parent education against social class and income

	Proportion by education		Obs
	Low	High	
Socio-economic class (NSSEC)			
Managerial and professional	0.20	0.80	1231
Intermediate	0.46	0.54	353
Small employers or self-employed	0.52	0.48	347
Lower supervisors and technical	0.63	0.37	345
Semi-routine and routine	0.75	0.25	746
N/A or not working	0.86	0.14	492
Income quintile groups			
Lowest first and second	0.82	0.18	1088
Third	0.60	0.40	719
Fourth	0.37	0.63	840
Fifth	0.54	0.46	867

Table A4.6: Background characteristics by parent education and sex: means

	All	Below Tertiary	Tertiary and above	Girls	Boys
Adolescent individual and demographic characteristics					
Male	0.46	0.45	0.48	0.00	1.00
Diff to 14 years old (in years)	-0.23	-0.24	-0.23	-0.24	-0.22
Ethnicity: White	0.88	0.87	0.88	0.89	0.86
Natural father in household	0.68	0.57	0.80	0.67	0.69
Natural mother in household	0.96	0.93	0.99	0.96	0.95
Has long-term illness, wave 6	0.16	0.17	0.14	0.16	0.15
No. of siblings in household	1.47	1.53	1.40	1.47	1.47
No. of people in household incl. adolescent	4.32	4.31	4.32	4.31	4.32
Word activity score out of 20	7.46	7.02	7.95	7.39	7.53
CITS, 9 months: mood	12.40	12.26	12.55	12.34	12.45
CITS, 9 months: approach/withdrawal	6.35	6.39	6.29	6.50	6.17
CITS, 9 months: adaptability	7.00	7.08	6.90	7.12	6.86
CITS, 9 months: regularity	5.28	5.42	5.13	5.22	5.36
Time diary controls					
TUD mode: App	0.69	0.70	0.68	0.74	0.64
TUD mode: Web	0.25	0.23	0.28	0.21	0.30
TUD mode: Paper	0.06	0.07	0.04	0.05	0.06
Parent characteristics					
Mother's age at birth					
11 to 19	0.07	0.13	0.01	0.08	0.06
20 to 29	0.44	0.52	0.36	0.43	0.46
30 to 39	0.46	0.33	0.61	0.46	0.46
40 plus	0.02	0.02	0.03	0.03	0.02
Parent has high depressive symptoms	0.05	0.07	0.02	0.06	0.04
Early socio-economic status, age 5					
Parent or partner has $\geq$ NVQ4 level	0.47			0.45	0.49
Housing tenure: Own/mortgage/loan	0.72	0.56	0.90	0.71	0.73
Highest NS-SEC in household					
None/not working	0.17	0.27	0.05	0.19	0.15
Managerial and professional	0.32	0.12	0.54	0.30	0.34
Intermediate	0.09	0.08	0.11	0.08	0.10
Small employers or self-employed	0.10	0.10	0.10	0.10	0.09
Lower supervisors or lower technical	0.10	0.12	0.08	0.09	0.11
Semi-routine or routine	0.23	0.32	0.12	0.24	0.21
Stratum indicators					
England - Advantaged	0.51	0.43	0.59	0.51	0.50
England - Disadvantaged	0.25	0.32	0.17	0.25	0.25
England - Ethnic	0.04	0.05	0.03	0.04	0.04
Wales - Advantaged	0.03	0.02	0.04	0.03	0.03
Wales - Disadvantaged	0.02	0.03	0.02	0.03	0.02
Scotland - Advantaged	0.07	0.05	0.08	0.06	0.07
Scotland - Disadvantaged	0.04	0.05	0.03	0.04	0.04
Northern Ireland - Advantaged	0.03	0.02	0.03	0.02	0.03
Northern Ireland - Disadvantaged	0.02	0.03	0.01	0.02	0.02
Observations	3364	1507	1857	1850	1514

Table A4.7: Parenting styles by parental education: means

Parenting questions	Below tertiary	$\geq$ Tertiary	Diff
Has rules about content on TV, age 7	0.53	0.57	-0.047**
Has rules about content on media, age 11	0.95	0.96	-0.003
Rules on early/late watching TV, age 7	0.85	0.87	-0.024*
Rules on early/late watching media, age 11	0.92	0.91	0.003
Observations	1535	1881	

Note: t-test of differences in means ***p<0.01, **p<0.05, *p<0.1.

4.8 Appendix B

4.8.1 Regression estimates with and without lagged scores

Table A4.8: Regression estimates for self-esteem, with and without lagged scores

	Weekday		Weekend	
	(1)	(2)	(1)	(2)
Social screen time	-0.081***	-0.088***	-0.062***	-0.063***
	(0.018)	(0.017)	(0.016)	(0.014)
Internet browsing	-0.101***	-0.078**	-0.071***	-0.063***
	(0.031)	(0.030)	(0.019)	(0.019)
Playing e-games	-0.025*	-0.025	-0.020*	-0.019
	(0.013)	(0.013)	(0.011)	(0.011)
Passive video	-0.029**	-0.029**	-0.008	-0.011
	(0.011)	(0.011)	(0.010)	(0.010)
Lagged self-esteem		0.269***		0.268***
		(0.021)		(0.019)
Observations	3,143	3,143	3,182	3,182
R-squared	0.157	0.226	0.156	0.226

Note: *** p<0.01, ** p<0.05, * p<0.1. Roman-wolf p-values after 500 replications. Column (1) reports estimates without lagged outcome variable, and column (2) reports estimates with the lagged outcome variable. All estimates control for individual, demographic, and family characteristics, stratum, mode used to answer TUD, full vector of "other" activities. The omitted activity is sleep, so estimates are interpreted as an additional hour in relation to sleep. Standard errors are reported in parentheses. All estimates are weighted using sampling weights for the whole of UK-level analysis in sweep 6, stratum divided into two for each region; advantaged or disadvantaged, and clustered at the ward level.

Table A4.9: Regression estimates on happiness in six domains, with and without lagged scores

	Life		Look		Family		Friend		School		School Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Weekday												
Social screen time	-0.070***	-0.077***	-0.068***	-0.070***	-0.083***	-0.087***	-0.034**	-0.038***	-0.052***	-0.050***	-0.046**	-0.051***
	(0.016)	(0.016)	(0.016)	(0.015)	(0.017)	(0.017)	(0.015)	(0.015)	(0.017)	(0.017)	(0.019)	(0.018)
Internet browsing	-0.107***	-0.097***	-0.080**	-0.065**	-0.128***	-0.126***	-0.104***	-0.103***	-0.097***	-0.089***	-0.077***	-0.063**
	(0.030)	(0.029)	(0.031)	(0.029)	(0.040)	(0.039)	(0.024)	(0.025)	(0.030)	(0.030)	(0.029)	(0.030)
Playing e-games	-0.016	-0.016	-0.034***	-0.033***	-0.002	-0.005	-0.013	-0.016	-0.014	-0.013	-0.006	-0.002
	(0.014)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)
Passive video	-0.032**	-0.032**	-0.051***	-0.052***	-0.019	-0.022*	-0.027*	-0.031**	-0.004	-0.004	-0.024	-0.023
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)
Lagged score		0.180***		0.201***		0.123***		0.134***		0.106***		0.192***
		(0.019)		(0.023)		(0.021)		(0.023)		(0.024)		(0.021)
Observations	3,143	3,143	3,143	3,143	3,143	3,143	3,143	3,143	3,143	3,143	3,143	3,143
R-squared	0.137	0.168	0.141	0.182	0.089	0.104	0.047	0.063	0.109	0.120	0.096	0.130
Weekend												
Social screen time	-0.033*	-0.035*	-0.046***	-0.046***	-0.036**	-0.035**	-0.036*	-0.037*	-0.037**	-0.036**	-0.041**	-0.041**
	(0.018)	(0.018)	(0.016)	(0.015)	(0.017)	(0.017)	(0.020)	(0.019)	(0.017)	(0.017)	(0.018)	(0.017)
Internet browsing	-0.045**	-0.038*	-0.058***	-0.060***	-0.055**	-0.052**	-0.025	-0.026	-0.015	-0.012	-0.029	-0.021
	(0.021)	(0.021)	(0.021)	(0.023)	(0.025)	(0.025)	(0.024)	(0.024)	(0.022)	(0.022)	(0.021)	(0.019)
Playing e-games	0.006	0.009	-0.020*	-0.021*	-0.002	-0.001	0.002	0.003	-0.000	0.001	-0.002	0.003
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)	(0.013)	(0.013)	(0.010)	(0.010)
Passive video	0.010	0.010	-0.011	-0.014	0.003	0.002	0.004	0.004	0.012	0.012	-0.005	-0.003
	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)	(0.011)	(0.013)	(0.013)	(0.012)	(0.011)
Lagged score		0.179***		0.210***		0.144***		0.130***		0.128***		0.194***
		(0.020)		(0.023)		(0.022)		(0.023)		(0.022)		(0.023)
Observations	3,182	3,182	3,182	3,182	3,182	3,182	3,182	3,182	3,182	3,182	3,182	3,182
R-squared	0.118	0.148	0.136	0.180	0.074	0.094	0.048	0.063	0.081	0.098	0.077	0.112

Note: *** p<0.01, ** p<0.05, * p<0.1. Refer to table notes in Table A4.8 above.

Table A4.10: Regression estimates on parent-reported behavioural problems, with and without lagged scores

	Total SDQ		Internalising		Externalising		Prosocial	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Weekday								
Social screen time	0.013	0.000	0.027	0.013	-0.007	-0.012	-0.046**	-0.047**
	(0.016)	(0.012)	(0.017)	(0.014)	(0.017)	(0.012)	(0.020)	(0.018)
Internet browsing	-0.058**	-0.050	-0.080***	-0.068**	-0.010	-0.012	-0.035	-0.026
	(0.029)	(0.022)	(0.030)	(0.023)	(0.028)	(0.021)	(0.030)	(0.029)
Playing e-games	-0.003	-0.008	-0.011	-0.011	-0.000	-0.008	-0.014	-0.014
	(0.013)	(0.012)	(0.012)	(0.010)	(0.014)	(0.012)	(0.014)	(0.012)
Passive video	-0.003	-0.005	-0.024*	-0.019	0.020	0.010	0.015	0.015
	(0.014)	(0.011)	(0.014)	(0.013)	(0.015)	(0.010)	(0.015)	(0.013)
Lagged score		0.613***		-0.545***		-0.647***		-0.488***
		(0.028)		(0.022)		(0.026)		(0.023)
Observations	3,143	3,143	3,143	3,143	3,143	3,143	3,143	3,143
R-squared	0.186	0.503	0.165	0.434	0.157	0.501	0.077	0.286
Weekend								
Social screen time	0.008	0.015	0.030*	0.030*	-0.018	-0.007	-0.044**	-0.033
	(0.015)	(0.010)	(0.015)	(0.012)	(0.016)	(0.011)	(0.017)	(0.017)
Internet browsing	-0.013	-0.007	-0.034	-0.027	0.011	0.013	-0.069**	-0.072**
	(0.022)	(0.016)	(0.025)	(0.017)	(0.020)	(0.015)	(0.028)	(0.027)
Playing e-games	-0.015	-0.001	-0.018	-0.007	-0.014	-0.002	-0.027**	-0.024
	(0.013)	(0.010)	(0.014)	(0.011)	(0.014)	(0.010)	(0.013)	(0.011)
Passive video	0.011	0.015	0.000	0.009	0.018	0.015*	-0.008	-0.011
	(0.010)	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)	(0.012)	(0.011)
Lagged score		0.654***		-0.550***		-0.681***		-0.507***
		(0.021)		(0.022)		(0.021)		(0.023)
Observations	3,182	3,182	3,182	3,182	3,182	3,182	3,182	3,182
R-squared	0.165	0.523	0.155	0.423	0.134	0.531	0.073	0.298

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Refer to table notes in Table A4.8 above.

4.9 Appendix D

4.9.1 Full regression estimates

Table A4.11: Full regression estimates for self-esteem

	Weekday	Weekend
Social screen time	-0.088***	-0.063***
	(0.017)	(0.014)
Internet browsing	-0.078**	-0.063***
	(0.030)	(0.019)
Playing e-games	-0.025	-0.019
	(0.013)	(0.011)
Passive video	-0.029**	-0.011
	(0.011)	(0.010)
Self-esteem, age 11	0.269***	0.268***
	(0.021)	(0.019)
Other time use activities		
Education	-0.020***	0.022*
	(0.008)	(0.013)
Physical activity/exercise	-0.001	0.003
	(0.011)	(0.010)
Work/leisure activities alone	-0.017	-0.018*
	(0.015)	(0.010)
Work/leisure activities with others	-0.010	-0.003
	(0.010)	(0.007)
Missing activity	-0.010*	-0.006
	(0.006)	(0.006)
Sex: Male	0.494***	0.533***
	(0.045)	(0.043)
Diff in age at interview from 14 years	-0.045	-0.019
	(0.062)	(0.060)
Ethnicity: White	-0.017	0.013
	(0.072)	(0.066)
Natural father in household	0.163***	0.136**
	(0.059)	(0.054)
Natural mother in household	0.156	0.149
	(0.108)	(0.103)
Has long-term illness	-0.254***	-0.262***
	(0.057)	(0.054)
No. of siblings in HH	0.116**	0.106**
	(0.045)	(0.042)
No. of people in HH	-0.079**	-0.067*
	(0.039)	(0.036)
Continued in next page		

Table A4.11 cont'd: Full regression estimates for self-esteem

Continued from previous page		
	Weekday	Weekend
Mother's age at birth (baseline: 11-19)		
20 to 29	-0.161	-0.100
	(0.111)	(0.113)
30 to 39	-0.112	-0.068
	(0.116)	(0.117)
40 plus	-0.114	0.035
	(0.172)	(0.189)
Early socio-economic characteristics, age 3 or below		
Highest parent education is NVQ4 or NVQ5	0.012	0.004
	(0.046)	(0.047)
Housing tenure: Own outright/mortgage/loan	0.074	0.071
	(0.061)	(0.063)
NSSEC (baseline: N/A not employed)		
Managerial and professional	0.009	0.060
	(0.076)	(0.077)
Intermediate	-0.163*	-0.130
	(0.088)	(0.088)
Small employers or self-employed	-0.009	-0.013
	(0.099)	(0.095)
Lower supervisors and technical	0.000	0.016
	(0.087)	(0.087)
Semi-routine and routine	-0.127*	-0.079
	(0.073)	(0.073)
Stratum (baseline: England, advantaged)		
England-Disadvantaged	0.045	0.083*
	(0.049)	(0.047)
England-Ethnic	0.180*	0.184**
	(0.096)	(0.087)
Wales-Advantaged	0.012	0.039
	(0.059)	(0.054)
Wales-Disadvantaged	0.031	0.090
	(0.066)	(0.059)
Scotland-Advantaged	0.122	0.143*
	(0.074)	(0.079)
Scotland-Disadvantaged	0.305***	0.311***
	(0.106)	(0.115)
Northern Ireland-Advantaged	0.089	0.097
	(0.077)	(0.079)
Northern Ireland-Disadvantaged	0.076	0.070
	(0.105)	(0.088)
Continued in next page		

Table A4.11 cont'd: Full regression estimates for self-esteem

Continued from previous page		
	Weekday	Weekend
Carey Infant Temperament Scale (CITS), 9 months		
Mood	-0.000	-0.001
	(0.005)	(0.005)
Approach/withdrawal	-0.003	-0.006
	(0.008)	(0.008)
Adaptability	-0.011	-0.001
	(0.007)	(0.007)
Regularity	0.004	0.001
	(0.007)	(0.007)
Number of days reported in TUD	0.160*	0.062
	(0.085)	(0.066)
TUD mode: Mobile Application	-0.068	0.046
	(0.045)	(0.088)
TUD mode: Online (PC)	0.000	0.095
	(.)	(0.091)
TUD mode: Paper	-0.105	0.000
	(0.093)	(.)
Main parent has high depressive symptoms	-0.339***	-0.297***
(Kessler)	(0.104)	(0.101)
Word activity score	0.003	0.005
	(0.008)	(0.008)
Constant	-0.135	-0.357
	(0.277)	(0.268)
Observations	3143	3182
R^2	0.226	0.226

Note: *** p<0.01, ** p<0.05, * p<0.1. Romano-wolf p-values reported for the coefficients of screen use on wellbeing. Standard errors are reported in parentheses. All estimates are weighted using sampling weights for the whole of UK-level analysis in sweep 6, stratum divided into two for each region; advantaged or disadvantaged, and clustered at the ward level.

Table A4.12: Full regression estimates for happiness in life, looks, and family

	Life		Look		Family	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	-0.077***	-0.035	-0.070***	-0.046***	-0.087***	-0.035
	(0.016)	(0.018)	(0.015)	(0.015)	(0.017)	(0.017)
Internet browsing	-0.097***	-0.038	-0.065	-0.060**	-0.126**	-0.052
	(0.029)	(0.021)	(0.029)	(0.023)	(0.039)	(0.025)
Playing e-games	-0.016	0.009	-0.033**	-0.021	-0.005	-0.001
	(0.013)	(0.011)	(0.012)	(0.011)	(0.013)	(0.010)
Passive video	-0.032	0.010	-0.052***	-0.014	-0.022	0.002
	(0.015)	(0.011)	(0.013)	(0.012)	(0.013)	(0.010)
Lagged score	0.180***	0.179***	0.201***	0.210***	0.123***	0.144***
	(0.019)	(0.020)	(0.023)	(0.023)	(0.021)	(0.022)
Other time use activities						
Education	-0.024***	0.004	-0.035***	-0.007	-0.018**	-0.001
	(0.008)	(0.014)	(0.008)	(0.014)	(0.007)	(0.014)
Physical activity/exercise	0.000	0.003	-0.017	-0.009	-0.007	-0.003
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Work/leisure activities alone	-0.023**	-0.003	-0.040***	-0.018	-0.030**	-0.017
	(0.011)	(0.011)	(0.013)	(0.012)	(0.013)	(0.015)
Work/leisure activities with others	-0.024**	0.002	-0.031***	-0.006	-0.022**	-0.007
	(0.010)	(0.009)	(0.009)	(0.009)	(0.011)	(0.009)
Missing activity	-0.022***	-0.002	-0.016**	-0.010	-0.013	-0.014*
	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Sex: Male	0.359***	0.361***	0.505***	0.543***	0.156***	0.158***
	(0.049)	(0.051)	(0.048)	(0.049)	(0.046)	(0.051)
Diff in age at interview from 14 years	-0.009	0.023	0.030	0.057	-0.002	-0.016
	(0.059)	(0.060)	(0.065)	(0.066)	(0.065)	(0.066)
Ethnicity: White	0.055	0.076	0.091	0.106	0.176***	0.167**
	(0.075)	(0.075)	(0.091)	(0.088)	(0.066)	(0.066)
Natural father in household	0.198***	0.199***	0.098*	0.068	0.251***	0.224***
	(0.066)	(0.061)	(0.059)	(0.056)	(0.073)	(0.071)
Natural mother in household	0.302**	0.280**	-0.037	-0.075	0.498***	0.440**
	(0.129)	(0.124)	(0.128)	(0.123)	(0.173)	(0.173)
Has long-term illness	-0.352***	-0.321***	-0.250***	-0.263***	-0.154**	-0.156**
	(0.058)	(0.058)	(0.060)	(0.060)	(0.065)	(0.065)
No. of siblings in HH	0.079	0.084	0.068	0.059	0.046	0.021
	(0.058)	(0.054)	(0.050)	(0.048)	(0.069)	(0.066)
No. of people in HH	-0.033	-0.045	-0.004	-0.002	-0.019	-0.016
	(0.050)	(0.047)	(0.045)	(0.044)	(0.064)	(0.062)

Continued in next page

Table A4.12 cont'd: Full regression estimates for happiness in life, looks, and family

Continued from previous page						
	Life		Look		Family	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Early socio-economic characteristics, age 3 or below						
Mother's age at birth (baseline: 11-19)						
20 to 29	-0.229*	-0.133	-0.310**	-0.137	-0.132	-0.057
	(0.125)	(0.121)	(0.124)	(0.121)	(0.144)	(0.133)
30 to 39	-0.195	-0.118	-0.252*	-0.117	-0.074	-0.027
	(0.130)	(0.126)	(0.133)	(0.127)	(0.147)	(0.134)
40 plus	0.008	0.083	-0.094	0.125	-0.030	0.053
	(0.164)	(0.169)	(0.163)	(0.179)	(0.161)	(0.167)
Highest parent education is NVQ4 or NVQ5	-0.081	-0.056	-0.017	-0.009	-0.128***	-0.121***
	(0.049)	(0.050)	(0.041)	(0.043)	(0.042)	(0.046)
Housing tenure: Own outright/mortgage/loan	0.102	0.075	0.083	0.067	0.055	0.076
	(0.070)	(0.068)	(0.068)	(0.069)	(0.063)	(0.064)
NSSEC (baseline: N/A not employed)						
Managerial and professional	0.111	0.136*	0.148*	0.171**	0.092	0.121
	(0.076)	(0.078)	(0.079)	(0.079)	(0.078)	(0.082)
Intermediate	-0.097	-0.063	-0.104	-0.115	0.001	0.015
	(0.090)	(0.087)	(0.105)	(0.101)	(0.091)	(0.092)
Small employers or self-employed	0.034	0.043	0.150*	0.154*	0.004	0.034
	(0.097)	(0.093)	(0.089)	(0.092)	(0.096)	(0.099)
Lower supervisors and technical	0.026	0.043	0.174*	0.151	0.011	0.064
	(0.098)	(0.098)	(0.094)	(0.094)	(0.103)	(0.101)
Semi-routine and routine	0.010	0.016	0.053	0.068	0.017	0.035
	(0.088)	(0.087)	(0.084)	(0.084)	(0.090)	(0.094)
Stratum (baseline: England, advantaged)						
England-Disadvantaged	-0.047	-0.015	0.030	0.042	-0.006	0.030
	(0.060)	(0.061)	(0.056)	(0.055)	(0.058)	(0.056)
England-Ethnic	-0.096	-0.040	0.165	0.209*	0.050	0.129
	(0.090)	(0.094)	(0.112)	(0.116)	(0.111)	(0.124)
Wales-Advantaged	0.017	0.019	0.092	0.093	0.065	0.087
	(0.069)	(0.072)	(0.064)	(0.067)	(0.092)	(0.086)
Wales-Disadvantaged	0.062	0.146*	-0.002	0.073	0.100	0.115
	(0.080)	(0.075)	(0.064)	(0.064)	(0.066)	(0.070)
Scotland-Advantaged	-0.029	-0.021	0.071	0.039	0.005	0.028
	(0.075)	(0.081)	(0.068)	(0.074)	(0.085)	(0.086)
Scotland-Disadvantaged	0.190	0.225*	0.210**	0.170*	0.082	0.124
	(0.125)	(0.115)	(0.088)	(0.091)	(0.110)	(0.113)
Northern Ireland-Advantaged	0.020	0.052	0.060	0.022	0.051	0.098
	(0.093)	(0.091)	(0.087)	(0.088)	(0.081)	(0.079)
Northern Ireland-Disadvantaged	-0.016	-0.092	0.118	0.097	0.027	0.036
	(0.101)	(0.107)	(0.097)	(0.097)	(0.102)	(0.094)
Continued in next page						

Table A4.12 cont'd: Full regression estimates for happiness in life, looks, and family

Continued from previous page						
	Life		Look		Family	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Carey Infant Temperament Scale (CITS), 9 months						
Mood	-0.005	-0.003	-0.005	-0.003	-0.005	-0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Approach/Withdrawal	-0.001	-0.002	0.000	0.001	-0.006	-0.008
	(0.008)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)
Adaptability	0.003	0.003	-0.014*	-0.010	-0.002	-0.007
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Regularity	-0.012	-0.013	-0.002	-0.006	-0.012	-0.012
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Number of days reported in TUD	0.097	0.059	-0.013	0.089	0.069	0.077
	(0.091)	(0.072)	(0.080)	(0.074)	(0.093)	(0.078)
TUD Mode: Mobile Application	-0.041	0.079	-0.008	0.093	-0.055	0.043
	(0.056)	(0.099)	(0.047)	(0.081)	(0.047)	(0.122)
TUD Mode: Online (PC)	0.000	0.060	0.000	0.080	0.000	0.071
	(.)	(0.110)	(.)	(0.085)	(.)	(0.129)
TUD Mode: Paper	-0.148	0.000	-0.072	0.000	-0.143	0.000
	(0.118)	(.)	(0.087)	(.)	(0.136)	(.)
Main parent has high depressive	-0.567***	-0.572***	-0.351***	-0.324***	-0.264**	-0.378***
symptoms (Kessler)	(0.127)	(0.133)	(0.128)	(0.112)	(0.131)	(0.129)
Word activity score	-0.017**	-0.018**	0.003	0.001	-0.024***	-0.025***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	-0.005	-0.428	0.348	-0.365	-0.213	-0.527*
	(0.308)	(0.261)	(0.295)	(0.276)	(0.287)	(0.302)
Observations	3143	3182	3143	3182	3143	3182
R^2	0.168	0.148	0.182	0.180	0.104	0.094

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses. Refer to table notes from Table A4.11.

Table A4.13: Full regression estimates for happiness in friends, school, and school work

	Friend		School		School Work	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	-0.038**	-0.037	-0.050**	-0.036	-0.051***	-0.041*
	(0.015)	(0.019)	(0.017)	(0.017)	(0.018)	(0.017)
Internet browsing	-0.103***	-0.026	-0.089**	-0.012	-0.063	-0.021
	(0.025)	(0.024)	(0.030)	(0.022)	(0.030)	(0.019)
Playing e-games	-0.016	0.003	-0.013	0.001	-0.002	0.003
	(0.015)	(0.012)	(0.014)	(0.013)	(0.013)	(0.010)
Passive video	-0.031	0.004	-0.004	0.012	-0.023	-0.003
	(0.015)	(0.011)	(0.014)	(0.013)	(0.014)	(0.011)
Lagged score	0.134***	0.130***	0.106***	0.128***	0.192***	0.194***
	(0.023)	(0.023)	(0.024)	(0.022)	(0.021)	(0.023)
Other time use activities						
Education	-0.015*	-0.002	-0.009	0.031**	-0.018**	0.020
	(0.008)	(0.016)	(0.008)	(0.015)	(0.009)	(0.016)
Physical activity/exercise	-0.020	-0.010	-0.001	0.004	0.009	0.012
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.012)
Work/leisure activities alone	-0.022*	-0.020	-0.020	0.001	-0.015	0.001
	(0.011)	(0.021)	(0.013)	(0.011)	(0.014)	(0.010)
Work/leisure activities with others	-0.017*	-0.004	-0.022*	-0.002	-0.006	-0.009
	(0.010)	(0.010)	(0.012)	(0.010)	(0.011)	(0.008)
Missing activity	-0.017	-0.025***	-0.034***	-0.028***	-0.020***	-0.016**
	(0.010)	(0.009)	(0.010)	(0.009)	(0.007)	(0.008)
Sex: Male	0.157***	0.129**	0.133***	0.130**	0.114**	0.108**
	(0.053)	(0.057)	(0.047)	(0.050)	(0.046)	(0.045)
Diff in age at interview from 14 years	-0.002	-0.003	-0.070	-0.004	-0.051	-0.028
	(0.066)	(0.066)	(0.066)	(0.067)	(0.068)	(0.069)
Ethnicity: White	0.044	0.042	-0.067	-0.075	0.025	0.034
	(0.081)	(0.086)	(0.084)	(0.081)	(0.074)	(0.074)
Natural father in household	0.084	0.098*	0.087	0.118**	0.158**	0.185***
	(0.056)	(0.053)	(0.065)	(0.059)	(0.064)	(0.063)
Natural mother in household	0.060	0.095	0.094	0.215	0.072	0.083
	(0.186)	(0.172)	(0.195)	(0.182)	(0.125)	(0.124)
Has long-term illness	-0.149**	-0.167**	-0.215***	-0.175***	-0.242***	-0.220***
	(0.065)	(0.066)	(0.068)	(0.058)	(0.058)	(0.059)
No. of siblings in HH	-0.038	-0.051	0.035	0.042	0.030	0.053
	(0.058)	(0.057)	(0.084)	(0.071)	(0.066)	(0.064)
No. of people in HH	0.051	0.046	0.000	-0.024	-0.015	-0.038
	(0.052)	(0.052)	(0.072)	(0.064)	(0.059)	(0.055)

Continued in next page

Table A4.13 cont'd: Full regression estimates for happiness in friends, school, and school work

Continued from previous page

	Friend		School		School Work	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Mother's age at birth (baseline: 11-19)						
20 to 29	-0.253*	-0.080	-0.333**	-0.259**	-0.386***	-0.255**
	(0.150)	(0.148)	(0.134)	(0.126)	(0.124)	(0.125)
30 to 39	-0.220	-0.092	-0.266**	-0.219*	-0.382***	-0.275**
	(0.146)	(0.141)	(0.133)	(0.127)	(0.126)	(0.128)
40 plus	-0.134	0.006	-0.328*	-0.234	-0.322*	-0.175
	(0.164)	(0.160)	(0.172)	(0.170)	(0.175)	(0.177)
Early socio-economic characteristics, age 3 or below						
Highest parent education is NVQ4 or NVQ5	-0.051	-0.063	0.040	0.037	0.015	0.016
	(0.048)	(0.047)	(0.044)	(0.046)	(0.046)	(0.049)
Housing tenure: Own outright/mortgage/loan	0.088	0.089	0.181***	0.154***	0.120*	0.066
	(0.073)	(0.070)	(0.064)	(0.059)	(0.065)	(0.066)
NSSEC (baseline: N/A not employed)						
Managerial and professional	0.032	0.018	0.113	0.069	0.074	0.108
	(0.088)	(0.088)	(0.078)	(0.078)	(0.078)	(0.077)
Intermediate	-0.065	-0.092	-0.116	-0.158*	-0.084	-0.084
	(0.106)	(0.104)	(0.097)	(0.093)	(0.097)	(0.092)
Small employers or self-employed	0.051	0.038	-0.036	-0.078	0.066	0.045
	(0.102)	(0.102)	(0.089)	(0.092)	(0.094)	(0.095)
Lower supervisors and technical	-0.068	-0.057	-0.040	-0.054	-0.030	-0.059
	(0.105)	(0.108)	(0.102)	(0.101)	(0.090)	(0.087)
Semi-routine and routine	0.004	-0.000	-0.019	-0.055	-0.039	-0.014
	(0.095)	(0.098)	(0.085)	(0.087)	(0.082)	(0.078)
Stratum (baseline: England, advantaged)						
England-Disadvantaged	0.004	0.023	-0.014	-0.036	-0.025	-0.011
	(0.065)	(0.063)	(0.064)	(0.064)	(0.068)	(0.066)
England-Ethnic	0.049	0.112	-0.053	-0.048	0.029	0.060
	(0.086)	(0.097)	(0.113)	(0.112)	(0.107)	(0.106)
Wales-Advantaged	0.114*	0.091	0.198***	0.162**	0.232**	0.193**
	(0.061)	(0.066)	(0.055)	(0.068)	(0.091)	(0.084)
Wales-Disadvantaged	0.130	0.162*	0.019	0.053	0.118	0.119
	(0.098)	(0.090)	(0.088)	(0.086)	(0.089)	(0.095)
Scotland-Advantaged	0.203***	0.213***	0.102	0.107	0.096	0.076
	(0.064)	(0.067)	(0.073)	(0.076)	(0.068)	(0.067)
Scotland-Disadvantaged	0.150	0.159	0.229*	0.242*	0.117	0.134
	(0.113)	(0.114)	(0.118)	(0.125)	(0.118)	(0.115)
Northern Ireland-Advantaged	0.217***	0.216***	0.124	0.135	0.045	0.068
	(0.084)	(0.080)	(0.097)	(0.088)	(0.085)	(0.090)
Northern Ireland-Disadvantaged	0.247***	0.196*	0.182**	0.039	0.103	0.035
	(0.095)	(0.105)	(0.090)	(0.092)	(0.102)	(0.096)

Continued in next page

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses. Refer to table notes from Table A4.11.

Table A4.13 cont'd: Full regression estimates for happiness in friends, school, and school work

Continued from previous page						
	Friend		School		School Work	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Carey Infant Temperament Scale (CITS), 9 months						
Mood	-0.010*	-0.007	-0.007	-0.003	-0.005	-0.003
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Approach/Withdrawal	-0.010	-0.014*	-0.020**	-0.021***	-0.002	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Adaptability	-0.009	-0.008	0.008	0.008	-0.012	-0.010
	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
Regularity	0.001	0.003	0.006	0.007	-0.001	-0.002
	(0.009)	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)
Number of days reported in TUD	0.074	-0.003	0.208**	0.164**	0.050	0.000
	(0.088)	(0.081)	(0.101)	(0.079)	(0.087)	(0.082)
TUD Mode: Mobile Application	-0.010	0.103	-0.022	0.067	-0.012	0.120
	(0.058)	(0.093)	(0.059)	(0.088)	(0.052)	(0.092)
TUD Mode: Online (PC)	0.000	0.075	0.000	0.049	0.000	0.133
	(.)	(0.105)	(.)	(0.098)	(.)	(0.095)
TUD Mode: Paper	-0.158	0.000	-0.086	0.000	-0.156*	0.000
	(0.107)	(.)	(0.096)	(.)	(0.091)	(.)
Main parent has high depressive	-0.237	-0.299*	-0.562***	-0.408***	-0.607***	-0.475***
symptoms (Kessler)	(0.170)	(0.156)	(0.146)	(0.145)	(0.171)	(0.177)
Word activity score	-0.000	-0.007	0.014*	0.006	0.030***	0.024***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.115	-0.089	-0.251	-0.439	0.086	-0.128
	(0.291)	(0.290)	(0.322)	(0.285)	(0.306)	(0.304)
Observations	3143	3182	3143	3182	3143	3182
R^2	0.063	0.063	0.120	0.098	0.130	0.112

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses. Refer to table notes from Table A4.11.

Table A4.14: Full regression estimates of parent-reported behavioural scores

	Total SDQ		Internalising		Externalising		Prosocial	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	0.000	0.015	0.013	0.030*	-0.012	-0.007	-0.047**	-0.033
	(0.012)	(0.010)	(0.014)	(0.012)	(0.012)	(0.011)	(0.018)	(0.017)
Internet browsing	-0.050	-0.007	-0.068**	-0.027	-0.012	0.013	-0.026	-0.072**
	(0.022)	(0.016)	(0.023)	(0.017)	(0.021)	(0.015)	(0.029)	(0.027)
Playing e-games	-0.008	-0.001	-0.011	-0.007	-0.008	-0.002	-0.014	-0.024
	(0.012)	(0.010)	(0.010)	(0.011)	(0.012)	(0.010)	(0.012)	(0.011)
Passive video	-0.005	0.015	-0.019	0.009	0.010	0.015*	0.015	-0.011
	(0.011)	(0.009)	(0.013)	(0.009)	(0.010)	(0.009)	(0.013)	(0.011)
Lagged score	0.613***	0.654***	-0.545***	-0.550***	-0.647***	-0.681***	-0.488***	-0.507***
	(0.028)	(0.021)	(0.022)	(0.022)	(0.026)	(0.021)	(0.023)	(0.023)
Other time use activities								
Education	0.006	0.027**	0.002	0.024*	0.004	0.021*	-0.005	-0.017
	(0.006)	(0.012)	(0.006)	(0.014)	(0.007)	(0.011)	(0.007)	(0.015)
Physical activity/exercise	0.023*	0.015	0.022**	0.022**	0.016	0.005	0.002	-0.006
	(0.012)	(0.010)	(0.010)	(0.010)	(0.013)	(0.009)	(0.014)	(0.012)
Work/leisure activities alone	0.020*	0.000	-0.007	-0.002	0.026**	-0.001	0.004	-0.009
	(0.012)	(0.010)	(0.009)	(0.011)	(0.010)	(0.008)	(0.014)	(0.010)
Work/leisure activities with others	0.008	0.013*	0.003	0.017**	-0.000	0.003	-0.011	-0.003
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.006)	(0.012)	(0.008)
Missing activity	-0.018*	0.004	-0.013*	0.001	-0.016	0.005	-0.008	-0.005
	(0.009)	(0.006)	(0.007)	(0.007)	(0.010)	(0.005)	(0.007)	(0.006)
Sex: Male	0.067*	0.078*	0.171***	0.181***	-0.070*	-0.060	-0.105**	-0.078*
	(0.038)	(0.041)	(0.040)	(0.043)	(0.036)	(0.038)	(0.047)	(0.043)
Diff in age at interview from 14 years	-0.060	-0.057	-0.021	-0.021	-0.088*	-0.058	-0.016	0.027
	(0.051)	(0.047)	(0.054)	(0.051)	(0.050)	(0.045)	(0.063)	(0.059)
Ethnicity: White	-0.098	-0.060	-0.078	-0.054	-0.105	-0.058	-0.107	-0.087
	(0.060)	(0.053)	(0.062)	(0.066)	(0.069)	(0.054)	(0.075)	(0.074)
Natural father in household	0.052	0.056	0.030	0.064	0.041	0.026	0.067	0.061
	(0.050)	(0.044)	(0.054)	(0.050)	(0.049)	(0.047)	(0.085)	(0.083)
Natural mother in household	0.067	0.072	0.081	-0.011	0.031	0.126	0.325	0.395*
	(0.126)	(0.117)	(0.140)	(0.126)	(0.114)	(0.114)	(0.209)	(0.212)
Has long-term illness	-0.237***	-0.204***	-0.302***	-0.295***	-0.183***	-0.126***	-0.041	-0.069
	(0.059)	(0.051)	(0.061)	(0.060)	(0.057)	(0.045)	(0.063)	(0.060)

Continued in next page

Table A4.14 cont'd: Full regression estimates of parent-reported behavioural scores

Continued from previous page

	Total SDQ		Internalising		Externalising		Prosocial	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
No. of siblings in HH	-0.009	-0.011	-0.026	-0.007	0.018	-0.017	-0.007	-0.014
	(0.046)	(0.043)	(0.051)	(0.049)	(0.059)	(0.053)	(0.095)	(0.091)
No. of people in HH	0.015	0.014	0.030	0.019	-0.028	0.006	-0.033	-0.029
	(0.040)	(0.040)	(0.047)	(0.044)	(0.052)	(0.050)	(0.090)	(0.085)
Mother's age at birth (baseline: 11-19)								
20 to 29	0.054	-0.083	-0.030	-0.045	0.077	-0.068	0.112	0.050
	(0.118)	(0.096)	(0.101)	(0.105)	(0.126)	(0.093)	(0.129)	(0.127)
30 to 39	0.126	-0.013	0.046	0.037	0.137	-0.021	0.166	0.113
	(0.121)	(0.099)	(0.105)	(0.107)	(0.126)	(0.094)	(0.123)	(0.127)
40 plus	0.031	-0.054	-0.051	-0.017	0.056	-0.053	0.057	0.137
	(0.132)	(0.118)	(0.136)	(0.137)	(0.134)	(0.115)	(0.166)	(0.155)
Early socio-economic characteristics, age 3 or below								
Highest parent education is NVQ4 or NVQ5	0.083**	0.076**	0.110***	0.103***	0.050	0.044	-0.012	-0.007
	(0.033)	(0.033)	(0.035)	(0.034)	(0.034)	(0.033)	(0.040)	(0.039)
Housing tenure: Own outright/mortgage/loan	0.001	0.010	0.008	0.013	0.004	0.004	0.031	0.013
	(0.047)	(0.048)	(0.052)	(0.054)	(0.052)	(0.047)	(0.059)	(0.057)
NSSEC (baseline: N/A not employed)								
Managerial and professional	0.059	0.043	0.073	0.064	0.059	0.012	0.181**	0.193**
	(0.065)	(0.059)	(0.066)	(0.065)	(0.064)	(0.062)	(0.089)	(0.090)
Intermediate	0.085	0.041	0.113	0.092	0.052	-0.028	0.224**	0.243**
	(0.067)	(0.066)	(0.069)	(0.071)	(0.072)	(0.076)	(0.102)	(0.103)
Small employers or self-employed	0.050	0.020	0.081	0.068	0.027	-0.034	0.121	0.091
	(0.072)	(0.067)	(0.075)	(0.076)	(0.072)	(0.071)	(0.092)	(0.095)
Lower supervisors and technical	0.013	-0.014	-0.039	-0.038	0.034	-0.039	0.118	0.126
	(0.086)	(0.084)	(0.081)	(0.084)	(0.091)	(0.088)	(0.100)	(0.100)
Semi-routine and routine	0.045	0.045	0.018	0.023	0.083	0.046	0.198**	0.206**
	(0.069)	(0.065)	(0.065)	(0.067)	(0.065)	(0.064)	(0.089)	(0.089)
Stratum (baseline: England, advantaged)								
England-Disadvantaged	-0.033	-0.024	-0.010	-0.004	-0.034	-0.039	-0.001	0.006
	(0.051)	(0.043)	(0.053)	(0.050)	(0.053)	(0.042)	(0.058)	(0.055)

Continued in next page

Table A4.14 cont'd: Full regression estimates of parent-reported behavioural scores

Continued from previous page

	Total SDQ		Internalising		Externalising		Prosocial	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
England-Ethnic	-0.106	-0.117	-0.063	-0.089	-0.096	-0.108	0.103	0.086
	(0.100)	(0.083)	(0.073)	(0.075)	(0.112)	(0.087)	(0.094)	(0.091)
Wales-Advantaged	-0.079	-0.052	-0.068	-0.049	-0.034	-0.021	-0.018	-0.017
	(0.060)	(0.054)	(0.059)	(0.053)	(0.063)	(0.052)	(0.068)	(0.064)
Wales-Disadvantaged	-0.029	-0.022	-0.055	-0.059	0.030	0.033	0.127*	0.124
	(0.054)	(0.054)	(0.058)	(0.056)	(0.055)	(0.063)	(0.073)	(0.081)
Scotland-Advantaged	0.033	0.015	0.070	0.049	0.014	0.005	-0.007	0.000
	(0.063)	(0.062)	(0.063)	(0.063)	(0.054)	(0.052)	(0.076)	(0.073)
Scotland-Disadvantaged	0.147	0.070	0.144	0.121	0.121	0.018	0.070	0.032
	(0.090)	(0.081)	(0.091)	(0.087)	(0.098)	(0.089)	(0.083)	(0.087)
Northern Ireland-Advantaged	-0.009	-0.060	0.013	-0.059	-0.024	-0.047	0.048	0.021
	(0.076)	(0.063)	(0.082)	(0.080)	(0.061)	(0.057)	(0.077)	(0.082)
Northern Ireland-Disadvantaged	0.069	0.088	0.099	0.155*	0.053	-0.015	0.094	0.053
	(0.083)	(0.095)	(0.080)	(0.087)	(0.082)	(0.089)	(0.085)	(0.101)
Carey Infant Temperament Scale (CITS), 9 months								
Mood	0.002	0.001	-0.002	-0.002	0.003	0.002	-0.001	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Approach/Withdrawal	0.003	0.004	0.005	0.004	0.000	0.002	-0.012	-0.010
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.009)	(0.008)
Adaptability	-0.009	-0.012*	-0.013*	-0.016**	0.000	-0.002	0.000	0.005
	(0.007)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)	(0.009)	(0.009)
Regularity	-0.009	-0.011	-0.004	-0.006	-0.010	-0.013*	-0.021**	-0.020**
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)
Number of days reported in TUD	0.050	0.047	0.032	-0.002	0.134	0.080	0.084	0.007
	(0.082)	(0.063)	(0.063)	(0.073)	(0.093)	(0.053)	(0.082)	(0.062)
TUD mode: Mobile Application	-0.008	0.111	0.010	-0.035	-0.053	0.216***	-0.002	-0.008
	(0.043)	(0.097)	(0.040)	(0.104)	(0.044)	(0.082)	(0.048)	(0.099)
TUD mode: Online (PC)	0.000	0.106	0.000	-0.059	0.000	0.241***	0.000	0.008
	(.)	(0.103)	(.)	(0.113)	(.)	(0.081)	(.)	(0.108)
TUD mode: Paper	-0.053	0.000	0.078	0.000	-0.172**	0.000	0.028	0.000
	(0.102)	(.)	(0.110)	(.)	(0.085)	(.)	(0.108)	(.)
Main parent has high depressive	-0.340**	-0.311***	-0.391***	-0.390***	-0.264*	-0.146	-0.227	-0.101
symptoms (Kessler)	(0.149)	(0.101)	(0.105)	(0.105)	(0.157)	(0.097)	(0.147)	(0.135)
Word activity score	0.015**	0.017***	0.004	0.008	0.018***	0.019***	-0.009	-0.004
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)
Constant	-0.387	-0.445*	-0.243	-0.181	-0.349	-0.521**	-0.227	-0.103
	(0.278)	(0.256)	(0.253)	(0.297)	(0.306)	(0.241)	(0.285)	(0.305)
Observations	3143	3182	3143	3182	3143	3182	3143	3182
R^2	0.503	0.523	0.434	0.423	0.501	0.531	0.286	0.298

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses. Refer to table notes from Table A4.11.

4.10 Appendix E: Regression estimates by subgroups

Table A4.15: Regression estimates for self-esteem, by subgroups

	Weekday				Weekend			
	High		Low		High		Low	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Social screen time	-0.089**	-0.126**	-0.056	-0.080*	-0.019	-0.122***	0.018	-0.08
	(0.028)	(0.038)	(0.036)	(0.027)	(0.024)	(0.024)	(0.028)	(0.025)
Internet browsing	-0.041	-0.185	-0.097	-0.078	-0.043	-0.038	-0.066*	-0.115
	(0.049)	(0.086)	(0.054)	(0.057)	(0.027)	(0.069)	(0.024)	(0.072)
Playing e-games	-0.007	-0.026	-0.043	-0.031	-0.017	-0.027	-0.021	-0.040
	(0.020)	(0.041)	(0.020)	(0.068)	(0.013)	(0.037)	(0.014)	(0.051)
Passive video	-0.005	-0.016	-0.063	-0.046*	-0.040	-0.001	-0.022	0.024
	(0.020)	(0.022)	(0.022)	(0.026)	(0.020)	(0.017)	(0.017)	(0.018)
Observations	830	929	600	810	778	867	562	747
R-squared	0.180	0.221	0.250	0.195	0.190	0.218	0.240	0.196

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, Romano-Wolf p-values after 500 replications. All estimates control for individual, demographic, and family characteristics, mode of survey, early years personality, stratum, full vector of "other" activities, and the respective lagged wellbeing scores. The omitted activity is sleep, so estimates are interpreted as an additional hour in relation to sleep. Standard errors are reported in parentheses. All estimates are weighted using sampling weights for the whole of UK-level analysis in sweep 6, stratum divided into two for each region; advantaged or disadvantaged, and clustered at the ward level. The Bonferroni p-values reported test whether the coefficients in the sub-samples are statistically significantly different from each other using 95% confidence intervals.

Table A4.16: Weekday regression estimates for happiness, by subgroups

	LIFE				LOOK				FAMILY			
	High		Low		High		Low		High		Low	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Social screen time	-0.104**	-0.118	-0.036	-0.063	-0.095**	-0.104*	-0.021	-0.054	-0.095**	-0.134***	-0.010	-0.105
	(0.033)	(0.041)	(0.034)	(0.032)	(0.026)	(0.033)	(0.037)	(0.028)	(0.031)	(0.031)	(0.026)	(0.037)
Internet browsing	-0.065	-0.227	-0.103	-0.054	-0.049	-0.125	-0.073	-0.018	-0.116**	-0.099	-0.103	-0.208
	(0.052)	(0.088)	(0.042)	(0.052)	(0.050)	(0.063)	(0.059)	(0.053)	(0.050)	(0.105)	(0.074)	(0.070)
Playing e-games	-0.018	0.009	-0.022	0.027	-0.008	-0.041	-0.044	-0.067	0.000	0.001	-0.004	0.030
	(0.018)	(0.043)	(0.022)	(0.064)	(0.018)	(0.066)	(0.017)	(0.045)	(0.017)	(0.033)	(0.021)	(0.043)
Passive video	-0.042	-0.032	-0.020	-0.032	-0.040*	-0.042	-0.069	-0.064	-0.065	-0.008	-0.017	-0.008
	(0.025)	(0.026)	(0.024)	(0.034)	(0.023)	(0.027)	(0.026)	(0.032)	(0.026)	(0.027)	(0.021)	(0.024)
Observations	830	929	600	810	830	929	600	810	830	929	600	810
R-squared	0.136	0.197	0.210	0.211	0.146	0.166	0.169	0.166	0.156	0.181	0.144	0.206
	FRIENDS				SCHOOL				SCHOOL WORK			
	High		Low		High		Low		High		Low	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Social screen time	-0.078**	-0.063	0.001	-0.020	-0.087**	-0.087**	0.076	-0.064	-0.093**	-0.112**	0.060	-0.043
	(0.027)	(0.032)	(0.037)	(0.029)	(0.023)	(0.026)	(0.038)	(0.032)	(0.029)	(0.031)	(0.045)	(0.031)
Internet browsing	-0.079**	-0.136	-0.156	-0.093	-0.053	-0.142	-0.100	-0.034	-0.076	-0.142	-0.041	-0.038
	(0.036)	(0.064)	(0.056)	(0.055)	(0.046)	(0.076)	(0.052)	(0.063)	(0.044)	(0.058)	(0.044)	(0.063)
Playing e-games	-0.033	-0.005	-0.014	0.004	-0.011	-0.037	-0.008	-0.045	0.003	-0.052	-0.017	0.088
	(0.016)	(0.049)	(0.025)	(0.065)	(0.016)	(0.044)	(0.024)	(0.078)	(0.020)	(0.049)	(0.022)	(0.068)
Passive video	-0.048	-0.012	-0.031	-0.040	-0.014	-0.009	-0.002	0.021	-0.023	-0.018	-0.014	-0.031
	(0.028)	(0.026)	(0.025)	(0.035)	(0.024)	(0.024)	(0.030)	(0.031)	(0.026)	(0.025)	(0.027)	(0.029)
Observations	830	929	600	810	830	929	600	810	830	929	600	810
R-squared	0.119	0.107	0.121	0.127	0.141	0.142	0.129	0.179	0.118	0.178	0.166	0.182

Note: *** p<0.01, ** p<0.05, * p<0.1. Refer to table notes in Table A4.15 above.

Table A4.17: Weekend regression estimates for happiness, by subgroups

	LIFE				LOOK				FAMILY			
	High		Low		High		Low		High		Low	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Social screen time	-0.024	-0.089***	0.034	-0.028	0.001	-0.102***	0.031	-0.067	-0.039	-0.069	0.054	-0.042
	(0.045)	(0.026)	(0.028)	(0.027)	(0.020)	(0.026)	(0.032)	(0.025)	(0.037)	(0.027)	(0.022)	(0.032)
Internet browsing	-0.019	-0.009	-0.075*	-0.097	-0.014	-0.062	-0.083**	-0.042	-0.075	0.038	-0.060	-0.097
	(0.030)	(0.053)	(0.031)	(0.062)	(0.036)	(0.072)	(0.027)	(0.065)	(0.035)	(0.046)	(0.042)	(0.063)
Playing e-games	-0.018	-0.030	0.027	-0.069	-0.019	-0.053	-0.015	-0.071	-0.003	-0.022	0.013	-0.026
	(0.013)	(0.046)	(0.011)	(0.071)	(0.014)	(0.044)	(0.014)	(0.048)	(0.014)	(0.043)	(0.012)	(0.052)
Passive video	-0.022	0.008	0.015	0.038	-0.043	0.001	-0.020	0.011	-0.011	0.015	0.026	0.016
	(0.021)	(0.016)	(0.017)	(0.021)	(0.019)	(0.016)	(0.017)	(0.022)	(0.016)	(0.015)	(0.016)	(0.023)
Observations	778	867	562	747	778	867	562	747	778	867	562	747
R-squared	0.121	0.173	0.231	0.209	0.151	0.170	0.162	0.157	0.136	0.159	0.140	0.197

	FRIENDS				SCHOOL				SCHOOL WORK			
	High		Low		High		Low		High		Low	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Social screen time	-0.016	-0.081**	0.043	-0.031	-0.005	-0.090***	0.037	-0.048	-0.039	-0.068***	0.036	-0.032
	(0.043)	(0.030)	(0.033)	(0.029)	(0.028)	(0.026)	(0.034)	(0.025)	(0.028)	(0.024)	(0.032)	(0.023)
Internet browsing	-0.013	0.016	-0.034	-0.008	-0.006	-0.000	-0.032	0.048	-0.041	0.001	0.001	0.040
	(0.027)	(0.045)	(0.046)	(0.049)	(0.024)	(0.043)	(0.047)	(0.053)	(0.027)	(0.036)	(0.037)	(0.062)
Playing e-games	0.001	0.056	0.021	-0.090	-0.020	-0.053	0.039**	-0.087	0.002	-0.021	0.009	-0.032
	(0.012)	(0.041)	(0.013)	(0.070)	(0.014)	(0.045)	(0.017)	(0.063)	(0.012)	(0.041)	(0.014)	(0.068)
Passive video	-0.027	0.006	0.035	0.024	0.009	0.009	0.021	0.008	0.007	-0.010	-0.003	0.000
	(0.021)	(0.017)	(0.017)	(0.019)	(0.015)	(0.015)	(0.021)	(0.024)	(0.019)	(0.015)	(0.019)	(0.022)
Observations	778	867	562	747	778	867	562	747	778	867	562	747
R-squared	0.118	0.099	0.108	0.129	0.136	0.122	0.120	0.154	0.110	0.165	0.164	0.180

Note: *** p<0.01, ** p<0.05, * p<0.1. Refer to table notes in Table A4.15 above.

Table A4.18: Regression estimates for parent-reported scores, by subgroups

	TOTAL SDQ				INTERNALISING				EXTERNALISING				PROSOCIAL			
	High		Low		High		Low		High		Low		High		Low	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Weekday																
Social screen time	0.006	-0.018	0.024	-0.001	0.009	-0.024	0.023	0.035	-0.000	0.000	0.012	-0.042**	-0.072	-0.027	-0.059	-0.035
	(0.016)	(0.017)	(0.032)	(0.020)	(0.017)	(0.024)	(0.034)	(0.025)	(0.017)	(0.016)	(0.034)	(0.021)	(0.029)	(0.024)	(0.048)	(0.030)
Internet browsing	-0.061	-0.133*	-0.059	0.009	-0.082	-0.209**	-0.049	0.017	-0.017	-0.026	-0.034	0.024	-0.055	0.013	0.001	-0.056
	(0.034)	(0.041)	(0.038)	(0.059)	(0.035)	(0.056)	(0.043)	(0.052)	(0.028)	(0.042)	(0.036)	(0.053)	(0.035)	(0.038)	(0.046)	(0.067)
Playing e-games	-0.031	-0.067	0.021	0.018	-0.021	-0.084	0.015	0.006	-0.029	-0.021	0.012	0.011	-0.014	-0.062	-0.001	-0.066
	(0.014)	(0.037)	(0.019)	(0.045)	(0.014)	(0.037)	(0.017)	(0.050)	(0.014)	(0.032)	(0.019)	(0.047)	(0.015)	(0.055)	(0.020)	(0.062)
Passive video	-0.001	-0.014	0.019	-0.004	-0.004	-0.032	0.005	-0.021	0.001	0.009	0.026	0.011	-0.004	-0.032	0.036	0.041*
	(0.017)	(0.017)	(0.025)	(0.019)	(0.016)	(0.018)	(0.027)	(0.025)	(0.018)	(0.018)	(0.025)	(0.017)	(0.020)	(0.021)	(0.028)	(0.023)
Observations	830	929	600	810	830	929	600	810	830	929	600	810	830	929	600	810
R-squared	0.532	0.415	0.521	0.574	0.478	0.331	0.460	0.510	0.510	0.465	0.514	0.561	0.314	0.321	0.380	0.322
Weekend																
Social screen time	0.035	-0.007	0.016	-0.005	0.051	0.003	0.018	0.006	0.005	-0.016	0.009	-0.018	-0.067	-0.006	0.018	-0.05
	(0.018)	(0.017)	(0.025)	(0.018)	(0.017)	(0.017)	(0.032)	(0.024)	(0.018)	(0.016)	(0.030)	(0.018)	(0.036)	(0.018)	(0.043)	(0.026)
Internet browsing	-0.026	-0.009	0.003	-0.051	-0.059***	-0.038	-0.007	-0.057	0.016	0.013	0.009	-0.029	-0.002	-0.077	-0.14	-0.144
	(0.022)	(0.032)	(0.022)	(0.046)	(0.020)	(0.039)	(0.024)	(0.053)	(0.022)	(0.025)	(0.023)	(0.045)	(0.018)	(0.054)	(0.064)	(0.057)
Playing e-games	-0.016	-0.047	0.002	-0.062	-0.016	-0.018	-0.011	-0.12	-0.011	-0.065	0.002	0.012	-0.035	-0.057	0.012	-0.033
	(0.012)	(0.031)	(0.014)	(0.042)	(0.012)	(0.032)	(0.014)	(0.058)	(0.012)	(0.038)	(0.013)	(0.035)	(0.013)	(0.029)	(0.015)	(0.035)
Passive video	0.008	0.004	0.018	0.014	0.007	-0.016	0.006	0.015	0.004	0.023	0.024	0.007	-0.005	0.001	0.019	-0.037
	(0.011)	(0.013)	(0.015)	(0.012)	(0.011)	(0.015)	(0.015)	(0.015)	(0.012)	(0.013)	(0.016)	(0.011)	(0.015)	(0.014)	(0.015)	(0.015)
Observations	778	867	562	747	778	867	562	747	778	867	562	747	778	867	562	747
R-squared	0.545	0.411	0.538	0.586	0.485	0.326	0.466	0.475	0.527	0.465	0.548	0.564	0.321	0.337	0.403	0.327

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Refer to table notes in Table A4.15 above.

4.11 Appendix G: Tercile hours on parent-reports

Table A4.19: Categorical estimates of screen time on parent-reported wellbeing, weekday

Parent-reported	Total SDQ	Internalising	Externalising	Prosocial
Social screen time				
Lowest tercile	0.006	0.047	-0.013	-0.034
	(0.041)	(0.044)	(0.040)	(0.052)
Middle tercile	0.021	0.086	-0.022	0.012
	(0.048)	(0.054)	(0.046)	(0.055)
Top tercile	0.018	0.095	-0.054	-0.161
	(0.049)	(0.059)	(0.055)	(0.081)
Internet				
Lowest tercile	0.041	0.009	0.028	0.012
	(0.091)	(0.114)	(0.065)	(0.106)
Middle tercile	-0.009	0.061	-0.087	-0.117
	(0.056)	(0.063)	(0.075)	(0.174)
Top tercile	-0.115	-0.168	-0.015	-0.023
	(0.076)	(0.081)	(0.072)	(0.101)
Playing e-games				
Lowest tercile	-0.152	-0.093	-0.152	-0.106
	(0.061)	(0.062)	(0.060)	(0.069)
Middle tercile	-0.069	-0.065	-0.050	-0.105
	(0.059)	(0.059)	(0.060)	(0.067)
Top tercile	-0.024	-0.048	-0.074	-0.036
	(0.073)	(0.063)	(0.078)	(0.075)
Passive video				
Lowest tercile	0.036	0.002	0.077	0.153
	(0.041)	(0.041)	(0.050)	(0.058)
Middle tercile	-0.047	-0.098	0.037	0.077
	(0.051)	(0.055)	(0.045)	(0.055)
Top tercile	0.033	-0.017	0.069	0.110
	(0.050)	(0.057)	(0.049)	(0.060)
Observations	3143	3143	3143	3143
R^2	0.505	0.436	0.504	0.290
p-values for equality of coefficients				
social low=mid	0.773	0.518	0.864	0.454
social mid=high	0.946	0.891	0.600	0.071
social low=high	0.824	0.424	0.470	0.140
internet low=mid	0.626	0.681	0.239	0.523
internet mid=high	0.206	0.021	0.447	0.626
internet low=high	0.189	0.210	0.652	0.814
e-games low=mid	0.302	0.735	0.162	0.991
e-games mid=high	0.519	0.800	0.764	0.433
e-games low=high	0.188	0.602	0.422	0.503
video low=mid	0.065	0.044	0.394	0.180
video mid=high	0.114	0.166	0.521	0.583
video low=high	0.937	0.719	0.888	0.492

Table A4.20: Tercile hours of screen time on parent-reported wellbeing, weekend

Parent-reported	Total SDQ	Internalising	Externalising	Prosocial
Social screen time				
Lowest tercile	0.109	0.129*	0.056	0.010
	(0.046)	(0.048)	(0.043)	(0.054)
Middle tercile	0.139***	0.203***	0.039	-0.039
	(0.039)	(0.046)	(0.037)	(0.052)
Top tercile	0.062	0.144**	-0.050	-0.101
	(0.048)	(0.051)	(0.051)	(0.074)
Internet				
Lowest tercile	-0.044	-0.000	-0.074	0.152
	(0.078)	(0.091)	(0.071)	(0.094)
Middle tercile	-0.071	-0.140	0.028	-0.049
	(0.085)	(0.092)	(0.074)	(0.104)
Top tercile	0.010	-0.057	0.077	-0.320
	(0.074)	(0.085)	(0.064)	(0.131)
Playing e-games				
Lowest tercile	0.067	0.065	0.040	-0.009
	(0.044)	(0.043)	(0.051)	(0.054)
Middle tercile	0.012	0.043	-0.029	-0.070
	(0.051)	(0.054)	(0.050)	(0.053)
Top tercile	0.015	-0.016	-0.006	-0.141
	(0.074)	(0.083)	(0.074)	(0.092)
Passive video				
Lowest tercile	0.004	-0.008	0.047	-0.006
	(0.049)	(0.050)	(0.052)	(0.069)
Middle tercile	0.107	0.051	0.149**	-0.009
	(0.049)	(0.052)	(0.048)	(0.055)
Top tercile	0.082	0.054	0.089	-0.050
	(0.050)	(0.052)	(0.052)	(0.062)
Observations	3182	3182	3182	3182
R^2	0.527	0.428	0.535	0.300
p-values for equality of coefficients				
social low=mid	0.550	0.199	0.697	0.433
social mid=high	0.145	0.337	0.104	0.416
social low=high	0.421	0.806	0.067	0.183
internet low=mid	0.811	0.281	0.267	0.158
internet mid=high	0.448	0.481	0.602	0.108
internet low=high	0.610	0.647	0.099	0.004
e-games low=mid	0.299	0.704	0.234	0.378
e-games mid=high	0.970	0.432	0.760	0.467
e-games low=high	0.476	0.353	0.547	0.196
video low=mid	0.029	0.218	0.036	0.957
video mid=high	0.601	0.946	0.186	0.488
video low=high	0.133	0.253	0.404	0.547

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard error in parentheses. Romano-Wolf p-values after 500 replications for main coefficient estimates. Estimates control for same control variables as in baseline estimates.

4.12 Appendix H: Regression estimates, constrained sample

Table A4.21: Regression estimates for self-esteem, constrained sample

	Weekday	Weekend
Social screen time	-0.086***	-0.069***
	(0.018)	(0.016)
Internet browsing	-0.091**	-0.066***
	(0.030)	(0.019)
Playing e-games	-0.025	-0.026
	(0.013)	(0.011)
Passive video	-0.024*	-0.014
	(0.012)	(0.010)
social=internet	0.890	0.899
social=e-gaming	0.002	0.013
social=passive video	0.001	0.002
internet=e-gaming	0.031	0.048
internet=passive video	0.030	0.009
e-gaming=passive video	0.967	0.364
Observations	2,928	2,928
R-squared	0.230	0.228

Note: *** p<0.01, ** p<0.05, * p<0.1. Romano-Wolf p-values after 500 replications for main coefficient estimates. All estimates control for individual, demographic, and family characteristics, stratum, full vector of "other" activities such as education, physical activity, work/leisure time with others and alone, and the respective lagged wellbeing scores. Standard errors are reported in parentheses. All estimates are weighted using sampling weights for the whole of UK-level analysis in sweep 6, stratum divided into two for each region; advantaged or disadvantaged, and clustered at the ward level.

Table A4.22: Regression estimates for self-reported wellbeing, constrained sample

	Life		Look		Family		Friend		School		School Work	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	-0.080***	-0.036	-0.076***	-0.051**	-0.092***	-0.042**	-0.041**	-0.042	-0.048**	-0.046	-0.055***	-0.039**
	(0.016)	(0.019)	(0.016)	(0.017)	(0.018)	(0.018)	(0.015)	(0.020)	(0.018)	(0.018)	(0.018)	(0.017)
Internet browsing	-0.102**	-0.046	-0.074*	-0.060**	-0.127**	-0.061*	-0.105***	-0.030	-0.096***	-0.013	-0.066*	-0.026
	(0.029)	(0.021)	(0.029)	(0.023)	(0.040)	(0.025)	(0.024)	(0.025)	(0.031)	(0.022)	(0.030)	(0.021)
Playing e-games	-0.024	-0.001	-0.035**	-0.029	-0.009	-0.007	-0.019	-0.005	-0.015	-0.001	0.000	-0.000
	(0.014)	(0.011)	(0.013)	(0.012)	(0.014)	(0.011)	(0.016)	(0.012)	(0.015)	(0.014)	(0.015)	(0.011)
Passive video	-0.03	0.009	-0.052***	-0.020	-0.022	0.003	-0.028*	-0.001	-0.001	0.010	-0.021	-0.006
	(0.015)	(0.012)	(0.014)	(0.013)	(0.013)	(0.011)	(0.015)	(0.012)	(0.015)	(0.013)	(0.014)	(0.011)
p-values of test of equality of coefficients												
social=internet	0.482	0.694	0.934	0.724	0.396	0.487	0.022	0.683	0.133	0.197	0.736	0.593
social=e-gaming	0.005	0.049	0.024	0.235	0.000	0.054	0.258	0.064	0.110	0.014	0.007	0.028
social=passive video	0.008	0.017	0.182	0.103	0.000	0.014	0.459	0.040	0.022	0.002	0.067	0.071
internet=e-gaming	0.014	0.036	0.186	0.164	0.004	0.026	0.002	0.316	0.008	0.581	0.041	0.210
internet=passive video	0.019	0.008	0.503	0.084	0.010	0.016	0.005	0.176	0.005	0.305	0.151	0.358
e-gaming=passive video	0.775	0.385	0.346	0.537	0.469	0.386	0.654	0.736	0.415	0.453	0.239	0.634
Observations	2,928	2,928	2,928	2,928	2,928	2,928	2,928	2,928	2,928	2,928	2,928	2,928
R-squared	0.166	0.152	0.185	0.177	0.112	0.098	0.067	0.068	0.102	0.099	0.131	0.126

Note: *** p<0.01, ** p<0.05, * p<0.1. Refer to table notes in Table A4.21 above.

Table A4.23: Regression estimates for parent-reported wellbeing, constrained sample

	TOTAL SDQ		INTERNALISING		EXTERNALISING		PROSOCIAL	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Social screen time	0.001	0.011	0.010	0.023	-0.007	-0.006	-0.034	-0.031
	(0.012)	(0.011)	(0.014)	(0.013)	(0.013)	(0.012)	(0.018)	(0.018)
Internet browsing	-0.055*	-0.008	-0.074**	-0.03	-0.014	0.016	-0.016	-0.074*
	(0.023)	(0.016)	(0.024)	(0.018)	(0.022)	(0.016)	(0.029)	(0.027)
Playing e-games	-0.010	-0.003	-0.015	-0.010	-0.006	-0.003	-0.010	-0.026
	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)	(0.010)	(0.012)	(0.013)
Passive video	-0.004	0.018	-0.016	0.011	0.011	0.018	0.023	-0.011
	(0.011)	(0.009)	(0.013)	(0.009)	(0.010)	(0.009)	(0.013)	(0.011)
social=internet	0.027	0.274	0.002	0.006	0.766	0.266	0.572	0.213
social=e-gaming	0.447	0.224	0.129	0.025	0.909	0.796	0.246	0.782
social=passive video	0.715	0.579	0.103	0.342	0.264	0.068	0.003	0.275
internet=e-gaming	0.050	0.760	0.015	0.262	0.698	0.304	0.852	0.091
internet=passive video	0.040	0.125	0.025	0.023	0.283	0.902	0.221	0.028
e-gaming=passive video	0.626	0.055	0.922	0.076	0.169	0.067	0.063	0.290
Observations	2,928	2,928	2,928	2,928	2,928	2,928	2,928	2,928
R-squared	0.516	0.516	0.418	0.418	0.529	0.528	0.292	0.293

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Refer to table notes in Table A4.21 above. Total difficulties, internalising behaviour, and externalising behaviour scales are reverse-coded. All negative estimates indicate worse behavioural problems for all scores.

Chapter 5

Conclusions

In this chapter, I first summarise the findings of Chapters 2 to 4. I discuss how the chapters contribute to our understanding of adolescents' time use, and the relationships between time use and socio-emotional competencies, and mental wellbeing. I then discuss the limitations of my work and the implications for data collection, policy, and future research. and policy.

5.1 Main findings and contributions

The findings show that in cases where risk and reward is high, and adolescents are constrained by resources and time as in developing countries, the 'zero-sum' theory or that work competes with the spheres of education (as per the work-life balance theory) seems to be present where more time in any form of work that reduces time for attending school is associated to poorer self-efficacy. On the other hand in countries where paid work during studies is more normalised at older adolescence (age 20/21), there may be gains to locus of control through paid work, suggesting support for the 'Reconciliation' approach, or that adolescents may be able to balance both spheres of work, leisure, and education. Unpacking leisure time in Chapter 4 to focus only on different types of screen use, I show that leisure is an activity often misunderstood for adolescents, which depending on the type of activity, can be negatively associated with adolescents' wellbeing.

5.1.1 More than simply 'good' and 'bad' activities

Focusing only on 'Activity' mechanisms, i.e., the types of activities adolescents do, my thesis provides new evidence about how work and leisure - activities that are less examined for adolescents than adults - are associated with socio-emotional competencies and mental wellbeing. In Chapter 2, I show how doing more paid work can be associated with poorer socio-emotional competencies in developing countries, exacerbating the problems of those who are disadvantaged. In Chapter 3, I show how for university students in the UK, engagement in paid work, rather than hours spent on paid work, may help improve socio-emotional competencies. This provides new evidence about student employment and socio-emotional competencies, not studied before. Given that self-efficacy and locus of control are similar in that they both measure an aspect of self-control and control and autonomy of one's actions and surroundings, it may be that there are specific characteristics of paid (or unpaid) work that is associated with these measures. In this latter case, the benefits of doing paid work may only be relevant to those who are already advantaged i.e., in higher education, but could potentially benefit those who are less advantaged within this already privileged group.

Leisure, whether broadly defined using the umbrella term 'leisure', or narrowly defined such as screen use, is not associated with improved socio-emotional competencies or mental wellbeing. In Chapter 4, I show that doing more of some leisure activities, such as using social networking sites, is associated with poorer adolescent self-esteem and happiness. In Chapter 2, I find that more time spent on leisure instead of attending school is associated with poorer socio-emotional competencies, but leisure is no more or less productive for skills when it reduces time spent on paid or domestic work in developing countries. This may also be due to leisure not being accurately defined, as in Chapter 2, where leisure included personal care or play, but could potentially include unobserved leisure time such as idling or doing nothing.

It is not straightforward to assess whether more time spent on an activity is 'good' or 'bad' for adolescent outcomes for two main reasons. First, it depends on how activities are differentiated under an umbrella category of an activity. I showed in Chapter 2 that domestic work is a more harmful type of work compared to paid economic work. In Chapter 3, only paid work during term-time was associated with an improved locus of control, not paid work during the holidays. In Chapter 4, more time spent on social screen activities and internet browsing was associated with worse adolescent mental wellbeing compared to playing e-games, or passive video viewing.

5.1.2 Time resource mechanisms

Second, in Chapters 2 and 4, I showed the importance of examining the full time budget over 24 hours. The associations between an activity of interest and adolescent outcomes differ depending on the other activities performed within the full time budget. In Chapter 2, I showed how more time spent on domestic or economic work instead of educational activities like attending school or studying outside school is associated with poorer socio-emotional competencies, which are in line with the zero-sum theory or work-life conflict. However, domestic or economic work, if associated with less time spent on leisure, is no more or less productive for adolescents' socio-emotional competencies, which is in line with the reconciliation approach or work-life balance. This shows that the types of activity traded off has implications for the types of mechanisms at play.

The benefits of activities like leisure and educational activities depend on the country. For example, educational activities such as attending school and studying outside school improve both self-efficacy and self-esteem for adolescents in Peru, but are statistically insignificant in the other three countries. These country differences demonstrate how adolescents in different countries have different elasticities of substitution across activities, and a one-size-fits-all policy may not be helpful in improving adolescents' outcomes.

In Chapter 4, I also show that the adolescents in the sample were primarily sedentary, and those who spend more time on screens were less likely to spend time on leisure activities in person, and less likely to do physical activities. Examining the full budget of activities provides better context into the kinds of activities adolescents are doing (and not doing), allowing us to better understand that the likely association between social screen time and adolescent wellbeing is driven by lower interaction with others and sedentary behaviour.

Thus, the relationship between time use and adolescent outcomes is not one just about "activity mechanisms" but also about "time resource mechanisms", especially in analyses where I can examine the adolescent's full time budget. Not using the full time budget means that the researcher makes assumptions about the activities that are contingent on the activity of focus, such as assuming more time in paid work is always associated with less time for education-related activities. Chapter 3 lacked the level of time use detail seen in Chapters 2 and 4. I only had information about paid work, but did not have the capability to examine whether, for example, time spent on paid work reduced the time that students had to attend classes, study, or relax.

5.1.3 Conceptualisation of time use across studies

My findings show that adolescents' time use reflects adolescents' autonomous decisions to an extent, i.e., their ability to make cost-benefit decisions, which may be influenced by their parents of peers, but ultimately reflect complex decision-making adolescents are capable of. How these activities such as engaging in work either to fund their lifestyle or to help their family, have differing associations with their socio-emotional competencies, which also depends on the country context, the alternative activities (if there is one), and vulnerability of groups.

My studies are an alternative to previous studies, where adolescents' time use are often examined in a prescriptive manner either due to data limitations, or societal concerns. For example, adolescents' leisure time is often ignored, or there is a strong focus on adolescents' paid work and their academic achievement, without considering the potential gains that may occur from a variety of activities adolescents may perform. My studies show this possibility; that there may be gains to be made from activities that are not just about attending school/college for adolescents, but must be analysed with care.

However, the majority of my findings are based on objective measures of time i.e., engagement and intensity of the activity and in relation to other activities within the day. My studies do not capture subjective time such as the feeling of being rushed or stressed, which could play an important role in relating time use and adolescent wellbeing. Studies have shown for adults, fragmented (e.g., short but frequent sets of activity) leisure time is related to greater stress (Sussman and Sekuler 2022). As adolescents of the 21st century move into a digital age of multi-tasking, it may be that subjective feelings about time may be more important than actual intensive time spent on a set of activities for adolescent wellbeing. Future work should consider examining subjective time for adolescents, especially during their transition into higher education, work, or family formation as these are events which will change their time structure significantly.

5.1.4 Conceptualisation of socio-emotional competencies and mental wellbeing

As a step towards contributing to our understanding and measurement of a more 'holistic' measure of adolescent wellbeing, this thesis paid special focus on adolescents' socio-emotional competencies and mental wellbeing. While this thesis does not aim to advance our understanding of these outcome measures, it shows the presence of significant relationships between adolescent time use in various activities and their wellbeing. In all chapters, the thesis focused on self-concepts such as self-esteem, self-efficacy, and locus of control, because of the crucial period of the adolescent age in reflecting self-image and identity. The chapter findings show the importance of adolescents' ability to learn how to be responsible and autonomous through activities such as paid work, but only in a safe environment, such as for university students in the UK. It shows the importance of autonomy in adolescents' wellbeing, the ability to feel that they have control over their surroundings and future. There may be characteristics of work (providing responsibility, or removing ability to control free or desired time) which may be driving this influence on self-efficacy and locus of control, but there may be many other activities which may enable this (physical activity in groups, structured play).

Chapter 4 examined a wider range of adolescents' mental wellbeing, mainly self-reported happiness and self-esteem, as well as reported behavioural scores by the parents. There is a strong correlation between self-esteem and self-image as shown in previous literature, usually driven by issues of body image (Vandenbosch, Fardouly, and Tiggemann 2022; Webster, Dunne, and Hunter 2021; Vincente-Benito and Valle Ramírez-Durán 2023). However, what was less clear is whether the differences in estimates between parental reports in behavioural problems and self-reports were because of the individual reporting it (and hence, differences in views of what is mental wellbeing) or if they are measuring two distinct types of mental wellbeing.

As discussed in the framework, competencies and mental wellbeing are not standalone measures, they are inter-connected by the environment, parental and peer support, and other factors. Much like co-morbidities in physical health as shown in public health studies, there are likely competencies that are interlinked. For example, Ngo, VanderLaan, and Aitken (2020) show that self-esteem (particularly peer and family self-esteem) and internalising behaviour are interlinked, and that self-esteem is also related to poorer clinical treatment outcomes. Examining the co-presence of wellbeing may also help us understand the differences in wellbeing reports by different observers, if there are correlations for certain types of measures but not for others. Future studies may want to examine the co-presence of wellbeing measures which may be related, either through structural equational modelling or machine learning.

5.1.5 Inequalities in time use and adolescent outcomes

Gender

Chapters 2 to 4 show that how adolescents spend time also reflect power and autonomy inequalities, particularly by gender and socio-economic status. The findings across all chapters show that socio-cultural norms and gender role socialisation are the main factors in explaining the division of time by gender in both the UK, as well as in the four developing countries. It is also likely that socio-biological factors (e.g., earlier puberty for girls than boys) play a role in exacerbating these inequalities.

In Chapters 2 and 4, girls spend more time in the so-called 'bad' activity; domestic work in developing countries, and social screen time in the UK. In both studies, there is an obvious division of time by gender; girls and boys do distinctly different activities whether it is in work or in leisure. These clear divisions suggest that adolescents are absorbing gender-typical expectations from a young age, and are influenced by the gender norms adopted by the adults and peers around them. In addition, Chapter 4 further elicits the potential role for early puberty in the more negative effects of social screen time for girls than boys. Girls reach physical maturation earlier than boys, and thus have a double-whammy challenge in navigating their social standing with regards to their image against their peers, along with the gendered culture of girls being depicted in more marginalised roles than boys.

There are several studies that suggest ways in attempts to better equalise gender norms. Chandra-Mouli, Plesons, and Amin (2018) summarised a list of programmes in various developing countries that are effective in equalising gender norms, such as direct interventions to improve beneficiaries' self-esteem and agency, supporting parents in promoting gender equitable attitudes, and incorporating gender equitable educational curricula in schools. The authors also highlight the importance of physiological changes in the adolescent brain for the effectiveness of these interventions, as this is a period when adolescents can think critically and challenge unequal gender norms. In a systematic review of global programmes that targeted gender inequality for adolescent health and wellbeing between 2000 and 2018, Levy et al. (2020) found that there were successful programmes to promote more gender equal norms through schools, the media, and engaging with community leaders. However, the authors argue that most of the interventions focused on improving the participants' attitudes, which do not necessarily lead to long-term change in their gender egalitarian perspectives. Hence, a collective effort at the policy, societal, school, and family-level is required to make real changes regarding this issue. Lamb and Koven (2019) argue that educational programmes, parenting, and encouraging girls to be active content creators on media (e.g., creating forums to empower girls) can help overcome the problem of sexualisation of girls. However, the authors also point out that the evidence is recent, and research tends to examine the risk for girls and boys, rather than examining how girls and boys can resist the risks. Future research should examine the ways in which girls and boys can have agency to navigate uncertain environments.

In Chapter 3, I found that in England, female university students engage in paid work more than male students, but there are no gendered differences in the association between work and locus of control. To date, it is still a puzzle as to why female students consistently work more than male students. Studies suggest that this is due to gendered preferences for types of work post-graduation (Goldin 2006; Boll, Mergele, and Zierow 2022), but it is unclear why it occurs during studies. Boll, Mergele, and Zierow (2022) show for German university students, female students work more than male students and still earn less than male students, explained by female students selecting into lower paid jobs during university such as working as waitresses or as office assistants. Since I did not observe the types of work, my findings can only conjecture that there are likely, again, gender socialisation for female adolescents that happen at a young age which persists into later adolescence, and studies also then show this perpetuates into adulthood in terms of their job preferences. This highlights the long-term implications gender socialisation can have in unequal adult outcomes.

Socio-economic background

Socio-economic background is observed in different forms in all three chapters (e.g., living in rural areas, have lower parental education, and less income), but still show distinct inequalities in time use. Much like in previous literature, adolescents from lower socio-economic backgrounds tend to engage more in paid or unpaid work rather than time in educational activities, often because of income constraints requiring them to work and study.

However, the relationship between adolescent's time use and their outcomes by socio-economic background depends again on the activity in question. In Chapter 2, there were few variations in the associations of domestic or economic work on adolescents' self-esteem or self-efficacy by urban or rural locality, and if present, moved in opposite directions depending on country analysed (e.g., work was associated with poorer self-efficacy for adolescents in rural areas in India, but poorer for adolescents in urban areas in Vietnam). In Chapter 4, both boys and girls with high parental education fare worse in their happiness in relation to social screen time, compared to adolescents with lower parental education. Girls with high parental education also and have worse internalising behaviour in relation to browsing the internet.

This is in contrast to previous studies which argue that socio-economic background can be a protective factor for certain vulnerable groups, such as through social support and parenting (Peng et al. 2021; Harter 1993). To an extent, it also shows more support for the 'Reconciliation Approach' rather than the 'Zero-sum' theory, as the detrimental associations of certain activities are not about the difficulties in trying to balance these activities (of which adolescents of lower socio-economic status tend to be more time constrained), but rather there is likely unobserved factors associated with specific activities that are disproportionately worse for adolescents from higher socio-economic status. In the case of screen activities, this may be the content on social media, how adolescents engage with social media (e.g., content creators rather than absorbers), and potentially exposure to multiple platforms on screens, which may be driving these negative associations with adolescents' mental wellbeing. For work in developing countries, it may be the types of work that I do not observe that drive the greater negative associations between work and self-efficacy in rural Indian areas, and urban Vietnamese areas.

This unconventional finding highlights that how adolescents' activities differ by socio-economic status may be more than just about income and time resource differences. The advent of the internet and technology, which has transformed how adolescents relate with peers and society, which may be influenced differently by adolescents' background, perhaps by their (in)ability to compete with others in the online realm. In my study, I only examined these variations by parental education. Given that socio-economic status, depending on the country, are made up of a variety of factors e.g., social class, income, and wealth, future research should examine how adolescents' time use varies by a comprehensive measure of socio-economic status, and their interactions with other important factors which may affect vulnerable groups like gender and ethnicity.

5.1.6 Limitations

Measurement issues

All of my outcome measures use socio-emotional competencies and/or mental wellbeing, captured in the survey data using Likert-type questions. In Likert-type questions, respondents indicate their level of agreement or disagreement with multiple statements relating to the concept. The outcome of interest is often measured as a sum score of the responses to these statements. The responses to these questions may be subject to several biases such as social desirability bias and anchoring. Social desirability bias is the tendency for a respondent to under report socially undesirable attitudes and behaviours either to fit in with others (e.g., the interviewer) or subconsciously to maintain a positive self-concept. Anchoring is when respondents interpret the Likert-type scales differently by using answers from the first few questions of a set of questions, as an anchor or reference point to answer the following questions within the set. These biases may lead to measurement error in the outcomes of interest.

While I cannot account for these biases, I used surveys designed to minimise them using neutrally worded questions or inter-mixing the items in the survey when measuring a concept. Questions about socio-emotional competencies are still relatively new in individual and household survey design, and are typically not collected across ages in longitudinal surveys. I recommend that future longitudinal birth cohort surveys should measure socio-emotional competencies and/or mental wellbeing during childhood and adolescence, much like in the three surveys I used. In particular, self-esteem and locus of control or self-efficacy can be measured from age 8 and up until early adulthood. There should also be survey research that examines the validity and reliability of these instruments, much like in the Young Lives survey (Yorke and Portela 2018).

Socio-emotional competencies have been criticised for having greater measurement error than cognitive skills, especially in developing countries. With regard to farmers in Western Kenya, Laajaj and Macours (2021) argue that socio-emotional competencies are difficult to measure accurately. The authors found that the measurement error for socio-emotional competencies is non-classical because correlations between questions are driven by how respondents answer depending on the phrasing of the questions. In a rural developing country setting, questions are typically asked by an interviewer because the respondents are unable to read. The authors found a large variation in responses across enumerators, which suggests difficulty in communicating the questions to the respondents. However, the authors also suggest ways to account for these problems, which I address in my chapters. Factor analysis can help increase the validity, reliability and predictive power of the socio-emotional competencies measures. Factor analysis helps determine the degree to which each survey item measured is associated with the socio-emotional skill measure of interest. Having a large set of items and repeated measures was also important for correcting for the measurement error. Of course, these suggestions are not a panacea, as Laajaj and Macours (2021) showed that a large amount of measurement error remained after these corrections.

The Young Lives survey provides technical reports that examine the validity of socio-emotional competencies measures. Given the lack of socio-emotional competencies measures in developing countries, future longitudinal birth cohort surveys should pilot the instruments from the Young Lives survey which are measured using the same set of questions in four developing countries. While there are challenges as discussed by Laajaj and Macours (2021), piloting these questions can provide explanations about which measures are most or least suitable for specific countries. Better data collection will improve future research about the returns on socio-emotional competencies in developing countries, and how these skills change across time.

Methodological alternatives

Since it is likely that both my outcomes of interest and adolescents' time use are correlated with unobserved characteristics, my findings could not determine if adolescent activities necessarily improve or worsen their outcomes. The relationships are also likely to be bidirectional i.e., time use can affect socio-emotional competencies or mental wellbeing and vice versa. There are other techniques to account for unobserved heterogeneity in panel data such as using fixed effects models or instrumental variables (IV). Fixed effects models assume that unobserved heterogeneities are time invariant and therefore controlling for them using longitudinal data produces causal estimates of time use on socio-emotional outcomes.

The use of fixed effects models does not overcome the issue of reverse causation since the models assume strict exogeneity i.e., any unobserved variables are not correlated with past, present, and future time use (Leszczensky and Wolbring 2019). In most of my analyses, I was unable to use fixed effects models because there was a lack of repeated measures of time allocation. In Chapter 2, I derived estimates using both fixed effects models and value-added models and showed that they were similar.

IV is a technique that uses a variable called an instrument, that is correlated with the predictor variable (time allocation), but uncorrelated with the outcome (socio-emotional competencies and/or mental wellbeing). The assumption is that the instrument exogenously changes adolescent time allocation, which allows the researcher to examine the exogenous change of time allocation on adolescents' outcomes. However, one needs a suitable instrument, and this is difficult to find. Additionally, because I am interested in a variety of activities from an adolescents' full time budget, I need one instrument per activity of interest. Even with a valid instrument, IV estimates produce local average treatment effects which may reflect non-representative estimates of the average treatment effect (Card 2001). Constrained by the data available to me, I use the most up-to-date techniques in the literature regarding children's time allocation to minimise these issues by controlling for as many individual-level and family-level characteristics as possible, and by using lagged outcome variables. I do not claim that my findings as causal, and I am careful to interpret my estimates with respect to my population of interest.

Attrition, missingness, and generalisability of findings

Issues of missingness is common across all chapters, which are driven by two main reasons. One, attrition across time in longitudinal studies, which usually is accounted by non-response models and adjusted for by weighting. Note that weighting is not a panacea, and adjusts distributions to account for potentially selective attrition. Two, the outcomes I examine are subjective, and when adolescents answer "Don't know" to a subjective question, we cannot determine whether that is an actual missing piece of information, or whether ths adolescent truly "did not know". As shown in the chapters, I attempt to account for selection, used alternative methods, conducted multiple imputations, and have conducted robustness checks by including and excluding "don't know" as a middle category in the analysis. These checks in general show similar narratives across the models, but with different sizes of magnitudes. Hence, it is likely that my analyses are robust, but we cannot account for the fact the estimate sizes may not be large, as they differ across estimations.

Since I utilize birth cohort data across all my chapters, these findings are not be broadly applicable to a wider population or range of ages for adolescents. Each of the datasets only ascribe to one cohort in each country. In the Young Lives data, the data was not weighted because the sample was intended to be pro-poor biased, as the aim of the surveys were to examine child poverty across time and cross-nationally. Hence, the findings should be interpreted in the context of children who were born in particularly poor areas of their country, and their transformations across time. For the UK birth cohort studies; the Next Steps and the Millennium Cohort Study, both are nationally representative samples of adolescents born in 1989/90 for the former, and adolescents born in 2000/02 for the latter. However again, these datasets only focus on the changes in the lives of these cohorts across time, which are not generalisable to adolescents of other ages within the UK.

Instead, these studies highlight the evolving dynamics of time use (such as the change in time use in the four developing countries between ages) and the longitudinal datasets allowed me to control for many early socio-demographic characteristics at the individual, parent-, and household-level, especially during childhood, which are important factors in the development of adolescents' socio-emotional competencies and mental wellbeing. While I do not fully exploit the longitudinal nature of the datasets, studies have shown that having these rich sets of controls are important in absorbing as much endogeneity in the analysis (Caetano, Kinsler, and Teng 2019).

5.2 Implications and relevance

5.2.1 Relevance of findings in advancing an integrative theory

My findings show that there are several potential pathways in which adolescent time use can relate to socio-emotional competencies, and adolescent wellbeing, which involve the integrative theories from psychology, sociology, and economics. In the literature across different disciplines, studies usually examine one aspect of the integrative framework I have proposed. Studies typically examine the effects of one (often 'socially prescribed') specified activity onto one specified outcome, few studies consider that there may be competencies developed through some more ‘unconventional’ activities, and studies have posited about “time resource” mechanisms without fully observing the full time budget. This thesis combines theories across disciplines to show that the way these relationships occur can be contextual and complex, depending on several main factors.

The findings across chapters, in different countries, show that the integrative theory is relevant in developing and developed countries. The cost-benefit issues of allocating activities are present in both countries, but how certain activities relate to socio-emotional competencies differ completely by risk (e.g., paid work and locus of control and self-efficacy in opposite directions.

As discussed above in the “Activity” mechanisms, the types of activity may relate differently to adolescents’ outcomes. My findings show that certain activities such as engaging in paid work during university could encourage adolescents’ belief and autonomy that they play an active role in their development, reflected by their locus of control, as posited by self-determination theory (SDT) in psychology, and links to the taxonomies by Schoon (2021) and Soto, Napolitano, and Roberts (2021). This also follows the theory of ’human capital development’, that adolescents can develop competencies through work experience or learning-by-doing. On the other hand, the SDT also helps explain how paid work may be related to poorer self-efficacy, especially in the context of risk (Rogoff 2003) where perhaps basic needs are not accounted for. In Chapter 2, adolescents’ engagement in paid work may reduce their self-esteem due diminished autonomy either due to the risky types of activities they’re involved in or the lack in being able to manage their ’other’ time.

In Chapter 2 in particular, my findings show through the “Time Resource” mechanism proposed, that it is not just the activity performed, but the activity replaced that matters. This brings together the discussions around the economic ‘zero-sum’ theories, and the sociological and psychological theories of the ’reconciliation’ approach, and ‘work-life’ balance or conflict. The findings show that adolescents can manage competing responsibilities in their lives (e.g., if they reduce time for leisure) to balance work and schooling, but if work conflicts with their education time, this is associated to poorer self-efficacy. Hence, the theory of work-life balance/conflict that is often used to explain the competing demands in life for adults is already reflected in adolescents at a young age. The context also matters, where work-life balance/conflict may be an issue for only adolescents aged 20/21 in developed countries like the UK, but can already be seen in developing countries for adolescents aged 15. Autonomy of adolescents' time (empowerment and dis-empowerment) can be reflected not just in the activities, but also in how they are able to use the rest of their time.

While the SDT helps explain how adolescents may gain competencies from certain activities such as paid work, there are also vulnerabilities across groups and types of activities. In Chapter 4, this can be seen in leisure activities; types of screen use where social screen time disproportionately affects girls' mental wellbeing and self-esteem negatively compared to boys, and higher parental education does not seem to be a protective factor. This is a puzzling finding, which may be explained by several elements of the activity that I do not examine in the study, such as content on screens, enjoyment of the activity, co-presence, timing of the activity, and so on. There are exciting future avenues of research that can examine both physical and mental associations associated with certain activities, such as the use of accelerometers, which can help detect biological changes such as the heart rate, helping us better understand how certain activities can help with adolescents' wellbeing.

What still needs unpacking are structured and unstructured leisure times, fragmented times of adolescents as the world becomes more technologically advanced, allowing multiple activities to be performed at once. The pandemic has shown that it is possible to have 'too much time' but also that the context matters, e.g., age, size of your house, etc.

5.2.2 Implications for data collection

The longitudinal birth cohort surveys I used in Chapters 2, 3, and 4 are high quality surveys which contain rich information about the adolescent, their family, and their environment, all of which enable me to analyse the adolescents' time use and their socio-emotional competencies or mental wellbeing across the life cycle. In Chapter 2, the Young Lives survey is one of few surveys about developing countries that contain longitudinal information about socio-emotional competencies and adolescents' time use, both reported by the adolescent themselves. In Chapter 3, I used the Next Steps survey which does not contain information about the types of paid work university students did, but is the only longitudinal birth cohort data in the UK that collects information about university students' engagement in work and their socio-emotional competencies. Finally, I use the MCS in Chapter 4, which is a nationally representative survey, and contains disaggregated information about adolescents' screen use, as well as rich longitudinal information about the adolescents, comparable to studies such as the Child Development Supplement (CDS) in the US Panel Study of Income Dynamics and the Longitudinal Survey of Australian Children (LSAC). While these datasets were useful for my analyses, more work can be done to improve current and prospective datasets.

Detailed adolescent time use information should be collected by longitudinal studies in developing countries because little is known about adolescent time use patterns in these countries. These information can help researchers examine inequalities in adolescent time use by economic, demographic, and gender compositions. Ideally, time use diaries should be administered as they help capture whether adolescents are engaged in economic work or chores, without needing to define the type of work specifically, which can become complex in informal labour market settings. Time diary questionnaires ask respondents to write both the length of time for which they performed an activity, and the activity that they performed. This disaggregated information can give researchers a better sense of which activities adolescents typically do, instead of pre-defining the groups of activities for them. For example, an adolescent who works for his/her uncle's business in exchange for goods for their parents may not consider their activity as market work. Seeking detailed time use information however comes at a cost to respondents and survey administrators. In cases where it is costly to obtain detailed information, surveys should at least aim for broad categories of activities that add up to 24 hours - much like in the Young Lives Survey - and differentiate between activities on a weekend and weekday, and disaggregate adolescents' leisure time e.g., time spent on screens, idle time, and time spent on hobbies.

There needs to be a more standardised way in which adolescent leisure time is measured in the UK. In Chapters 3 and 4 for which I used UK longitudinal birth cohort data, leisure time was measured differently across sweeps for the older birth cohort (Next Steps), and while improvements have been made for the younger birth cohort (MCS), it may not be collected in their latest sweep (the next sweep of MCS data will be published in 2025). In Next Steps, some retrospective information about leisure or spare time was collected at ages 14, 15, 17 and 25, but not at ages 16, 18, 19 or 20. The types of leisure information collected also varied at each age. At ages 14 and 15, the question was "How do you mainly spend your free time?" and the responses ranged from "Spend time with friends" to "Spend time with family". At age 17, the question about leisure was phrased as "Here are a list of things people do in their spare time. Can you please tell me which, if any, you have been to or done in the last four weeks?". The responses ranged from going to an amusement arcade to playing a musical instrument. The MCS consistently collect retrospective adolescent time use at the ages of 11, 14, and 17, but may not collect it at age 22 (as the final questionnaires are not finalised at the time of writing). Distinctly, both datasets lack time use information about domestic chores and unpaid care work at home. I recommend that future data collection for UK longitudinal birth cohort studies should have standardised measures of leisure time from age 10 to adulthood. Not collecting this information leaves researchers to make assumptions about adolescent behaviour, and misses potential hidden gendered time use inequalities.

UK surveys should collect information about adolescents' paid work, whether or not they are in education, from compulsory-schooling age to higher education. In the UK, this information is overlooked for adolescents who continue schooling after the compulsory-schooling age, or enter university. Obtaining this information is important to understand the costs and benefits of paid work during studies, as I discussed in the literature review in Chapter 3, as well as students' intentions to stay in education. For the 2019 UK Postgraduate Taught Experience Survey, Neves and Leman (2019) reported that "difficulty balancing study and other commitments" was the top reason for postgraduate taught students considering leaving education. Neves and Leman (2019) comment that the "commitments" referred to were "likely to include spending time working for pay, among other responsibilities." Despite this acknowledgement, it remains difficult to find information about UK students' and/or adolescents involvement in paid work whether from the Office for National Statistics or HESA. At the very least, there should be one question in HESA which asks whether or not the student has worked during term-time.

5.2.3 Policy relevance and future research

My findings add to the broader policy discourse surrounding the risks associated with adolescence. Public discourse about the activities that adolescents do tend to be driven by strongly-felt worries, focusing on the threat of a perceived bad activity i.e., paid work or playing too many video games. My findings show that determining what is good or bad is complicated. There needs to be discussions about how a bad activity is necessarily defined, and whether shifting time away from the bad activity translates to a better use of time. For example, does a policy to reduce paid child labour in developing countries necessarily help adolescents spend more time attending school? Does a policy banning adolescents from playing video games on a weekday (like the ban in China) necessarily translate to more time spent doing homework? In order to answer such questions, more information needs to be collected about adolescent time use, as discussed in the previous sub-section.

There is also a research gap in terms of utilising the time use diaries that are available. Hunt and McKay (2015) showed in their review of adolescent health studies between 1990 and 2014, which used time use diaries, that the majority of studies examined discrete behaviours instead of using the full 24-hour set of activities. Banthorpe et al. (2020), who used the MCS time diaries, also examined stylised information (social media) but did not consider the full set of activities that adolescents did. Future research should examine the ways in which we can incorporate the full time budget in examining adolescents' lifestyle patterns, which could help uncover the extent activities co-exist or trade-off against each other.

I support the call by scholars to use subjective wellbeing measures as indicators to monitor progress, inform policy design, and appraise policy. In the UK over the past decade, the inclusion of these indicators has gained recognition, such as the launch of the first World Happiness Report in 2012, the launch of the What Works Centre for Wellbeing in 2013, an independent body that provides evidence-based policy recommendations about wellbeing to the government, and the publication of the first set of wellbeing measures at the national level in 2019 by the Office for National Statistics. Layard et al. (2022) argue in their manifesto that all employers and schools should measure the wellbeing of individuals they affect, at least once a year.

Policy practitioners should collect and publish data on adolescent wellbeing and socio-emotional competencies, especially for indicators used to compare across countries or institutions. These questions could be added to surveys that are already in place for students. For example, international indicators such as the Programme for International Student Assessment (PISA) use students' performances in cognitive tests (i.e., reading, mathematics, and science) as their main indicator to compare student quality across countries. The PISA survey also collects other information about the student, such as their characteristics, and their parents, teachers, and schools, but these indicators are not the primary measure used to assess student quality. In the most recent 2018 PISA survey, the student questionnaires included wellbeing measures such as life satisfaction, perceptions of body image, psychological distress, and hedonic and eudemonic wellbeing (OECD 2018), but no measures of socio-emotional competencies. In future PISA surveys, I recommend that the survey measures students' self-esteem and self-efficacy scores at the least, since these measure self-concepts developed during adolescence. These measures could be readily incorporated into the PISA survey since the survey already includes related measures such as self-efficacy regarding global issues.

Students' mental wellbeing should be included as a key indicator of student progress in institutions that collect and publish information about higher education, such as the UK HESA. Currently, HESA only reports two measures of student wellbeing, which are mental health conditions recorded under disability measures, and student satisfaction surveys about the course/university administered by the National Student Survey and Advance HE. Wellbeing was also measured differently across the 2019 student satisfaction surveys by Advance HE, before Covid-19. Two surveys – the Postgraduate Research Experience Survey (PRES) and the Student Academic Experience Survey (SAES) for undergraduates – have wellbeing measures of students' life satisfaction, life being worthwhile, happiness, and low anxiety. However, this information was not published in the third survey, the Postgraduate Taught

Experience Survey (PTES). These agencies and bodies should collect and publish standardised measures of student wellbeing across time. Such indicators are useful to measure educational institutions' quality, and could help inform future policies to enhance students' wellbeing during higher education.

Livingstone et al. (2017) reviewed the literature about adolescents' screen use in low- and middle-income countries and found that the data about adolescents' digital media use are difficult to find and of low quality. The authors found that the evidence is unequal across countries (e.g., the majority of studies about Africa are about South Africa), and is mostly about older adolescents and university students rather than adolescents between the ages of 10 and 14. A scoping review by Ghai et al. (2021) showed how there is a lack of representation of minority ethnic groups and samples from the Global South in regard to adolescent social media use and depression. Surveys in developing countries need to collect information about adolescents' screen time, and future research should examine how adolescent screen use relates to their socio-emotional competencies or mental wellbeing. These data and research findings could help policy practitioners determine ways to improve digital access in developing countries in order to maximise their benefits and minimise the risks.

References

Abebe, Tatek. 2007. "Changing Livelihoods, Changing Childhoods: Patterns of Children's Work in Rural Southern Ethiopia." *Children's Geographies* 5 (1-2): 77–93.

Abrahams, Loes, Gina Pancorbo, Ricardo Primi, Daniel Santos, Patrick Kyllonen, Oliver P John, and Filip De Fruyt. 2019. "Social-emotional skill assessment in children and adolescents: Advances and challenges in personality, clinical, and educational contexts." *Psychological Assessment* 31 (4): 460–473. https://doi.org/10.1037/pas0000591.

Achen, Christopher H. 2000. *Why lagged dependent variables can suppress the explanatory power of other independent variables.* Annual Meeting of the Political Methodology Section of the American Political Science Association, UCLA. http://www-personal.umich.edu/~franzese/Achen.2000.LDVstealingExplanPower.pdf.

Adam, Barbara. 1994. *Time and Social Theory.* Wiley.

Ajayi, Kehinde, Smita Das, Clara Delavallade, Tigist Ketema, and Lea Rouanet. 2023. *Gender differences in socio-emotional skills and economic outcomes.* Policy Research Working Paper 10197. The World Bank.

Almlund, Mathilde, Almlund L. Duckworth, James J. Heckman, and Tim D. Kautz. 2011. "Personality and Psychology Economics." In *Handbook of the Economics of Education,* 1st ed., edited by Eric Hanushek, Stephen Machin, and Ludger Woessmann, vol. 4. Amsterdam: Elsevier. https://doi.org/10.1016/B978-0-444-63459-7.10000-4.

American Psychological Association. 2007. *Report of the APA Task Force on the sexualization of girls.* American Psychological Association Report. https://www.apa.org/pi/women/programs/girls/report-full.pdf.

Andersen, Susan L., and Martin H. Teicher. 2006. "Stress, sensitive periods and maturational events in adolescent depression." *Trends in Neurosciences* 31 (4): 183–191. https://doi.org/10.1016/j.tins.2008.01.004.

Anderson, Craig A., Akiko Shibuya, Nobuko Ihori, Edward L. Swing, Brad J. Bushman, Akira Sakamoto, Hannah R. Rothstein, and Muniba Saleem. 2010. "Violent video game effects on aggression, empathy, and prosocial behavior in Eastern and Western countries: A meta-analytic review." *Psychological Bulletin* 136 (2): 151–173. https://doi.org/10.1037/a0018251.

Apel, Robert, Shawn D. Bushway, Raymond Paternoster, Robert Brame, and Gary Sweeten. 2008. "Using state child labor laws to identify the causal effect of youth employment on deviant behavior and academic achievement." *Journal of Quantitative Criminology* 24 (4). https://doi.org/10.1007/s10940-008-9055-5.

Appel, Helmut, Alexander L Gerlach, and Jan Crusius. 2016. "The interplay between Facebook use, social comparison, envy, and depression." *Current Opinion in Psychology* 9:44–49. https://doi.org/10.1016/j.copsyc.2015.10.006.

Arrow, Kenneth. 1962. "Economic Welfare and the Allocation of Resources for Invention." In *The Rate and Direction of Inventive Activity: Economic and Social Factors,* 609–626. National Bureau of Economic Research, Inc. https://EconPapers.repec.org/RePEc:nbr:nberch:2144.

Arsandaux, Julie, Emilie Boujut, Réda Salamon, Christophe Tzourio, and Cédric Galéra. 2023. "Self-esteem in male and female college students: Does childhood/adolescence background matter more than young-adulthood conditions?" *Personality and Individual Differences* 206:112117. ISSN: 0191-8869. https://doi.org/doi.org/10.1016/j.paid.2023.112117. https://www.sciencedirect.com/science/article/pii/S0191886923000405.

Ashenfelter, Orley. 1978. "Estimating the effect of training programs on earnings." *The Review of Economics and Statistics* 60 (1): 47–57. https://doi.org/10.2307/1924332.

Attanasio, Orazio, Sarah Cattan, Emla Fitzsimons, Costas Meghir, and Marta Rubio-Codina. 2020. "Estimating the production function for human capital: Results from a randomized control trial in Colombia." *American Economic Review* 110 (1): 48–85. https://doi.org/10.1257/aer.20150183.

Attanasio, Orazio, Costas Meghir, and Emily Nix. 2020. "Human Capital Development and Parental Investment in India." *Review of Economic Studies* 87 (6): 2511–2541. https://doi.org/10.1093/restud/rdaa026.

Aufseeser, Dena, Michael Bourdillon, Richard Carothers, and Olivia Lecoufle. 2018. "Children's work and children's well-being: Implications for policy." *Development Policy Review* 36 (2): 241–261. https://doi.org/10.1111/dpr.12215.

Baert, S, B Neyt, E Omey, and D Verhaest. 2022. "Student work during secondary education, educational achievement, and later employment: A dynamic approach." *Empirical Economics* 63 (1): 1605–1635. https://doi.org/10.1007/s00181-021-02172-7.

Ball, Stephen J. 1984. "Beachside reconsidered: reflections on a methodological apprenticeship." In *The Research Process in Educational Settings,* 69–96. Routledge.

Bandura, Albert, William H. Freeman, and Richard Lightsey. 1999. "Self-efficacy: The exercise of control." *Journal of Cognitive Psychotherapy* 13:158–166. https://doi.org/10.1891/0889-8391.13.2.158.

Banthorpe, Amber, Lizzy Winstone, Becky Mars, and Paul Moran. 2020. "Is social media screen time really associated with poor adolescent mental health? A time use diary study." *Journal of Affective Disorders* 274:864–870. https://doi.org/10.1016/j.jad.2020.05.106.

Bauman, Adrian, Michael Bittman, and Jonathan Gershuny. 2019. "A short history of time use research; implications for public health." *BMC Public Health* 19 (2). https://doi.org/10.1186/s12889-019-6760-y.

Becker, Birgit. 2022. “Educational ICT use outside school in the European Union: disparities by social origin, immigrant background, and gender.” *Journal of Children and Media* 16 (1): 1–20. https://doi.org/10.1080/17482798.2021.1902359.

Becker, Gary S. 1964. *Human capital: A theoretical and empirical analysis, with special reference to education.* New York: National Bureau of Economic Research; distributed by Columbia University Press.

Bellemare, Marc F., Takaaki Masaki, and Thomas B Pepinsky. 2017. “Lagged Explanatory Variables and the Estimation of Causal Effect.” *The Journal of Politics* 79 (3): 949–963. https://doi.org/10.1086/690946.

Ben-Porath, Yoram. 1967. “The production of human capital and the life cycle of earnings.” *Journal of Political Economy* 75 (4): 352–365. http://www.jstor.org/stable/1828596.

Berryman, Chloe, Christopher J. Ferguson, and Charles Negy. 2018. “Social Media Use and Mental Health among Young Adults.” *The Psychiatric Quarterly* 89 (2): 307–314. https://doi.org/10.1007/s11126-017-9535-6.

Best, Paul, Roger Manktelow, and Brian Taylor. 2014. “Online communication, social media and adolescent wellbeing: A systematic narrative review.” *Children and Youth Services Review* 41 (C): 27–36. https://doi.org/10.1016/j.childyouth.2014.

Bickham, David S., Yulin Hswen, and Michael Rich. 2015. “Media use and depression: exposure, household rules, and symptoms among young adolescents in the USA.” *International Journal of Public Health* 60:147–155. https://doi.org/10.1007/s00038-014-0647-6.

Biswas-Diener, Robert, Todd B. Kashdan, and Laura A. King. 2009. “Two traditions of happiness research, not two distinct types of happiness.” *The Journal of Positive Psychology* 4 (3): 208–211. https://doi.org/10.1080/17439760902844400.

Bleidorn, Wiebke, Ruben C Arslan, Jaap J A Denissen, Peter J Rentfrow, Jochen E Gebauer, Jeff Potter, and Samuel D Gosling. 2016. "Age and gender differences in self-esteem—A cross-cultural window." *Journal of Personality and Social Psychology* 111 (3): 396–410. https://doi.org/10.1037/pspp0000078.

Boll, Paul D., Lukas Mergele, and Larissa Zierow. 2022. "The gender pay gap in university student employment." *Empirical Economics* 63:2253–2313. https://doi.org/10.1007/s00181-021-02194-1.

Bolton, Paul. 2022. *The value of student maintenance support.* Briefing Paper No. 00916. House of Commons Library: UK Parliament. https://researchbriefings.files.parliament.uk/documents/SN00916/SN00916.pdf.

Booker, Cara L., Yvonne J. Kelly, and Amanda Sacker. 2018. "Gender differences in the associations between age trends of social media interaction and well-being among 10-15 year olds in the UK." *BMC Public Health* 18 (321). https://doi.org/10.1186/s12889-018-5220-4.

Borga, Liyousew G. 2019. "Children's own time use and its effect on skill formation." *The Journal of Development Studies* 55:876–893. https://doi.org/10.1080/00220388.2018.1499893.

Borga, Liyousew G., Daniel Münich, and Lubomir Kukla. 2021. "The socioeconomic gradient in child health and noncognitive skills: Evidence from the Czech Republic." *Economics & Human Biology* 43:101075. ISSN: 1570-677X. https://doi.org/10.1016/j.ehb.2021.101075.

Borghans, Lex, Angela Lee Duckworth, James J. Heckman, and Bas ter Weel. 2008. "The Economics and Psychology of personality traits." *Journal of Human Resources* 43 (4): 972–1059. https://doi.org/10.3368/jhr.43.4.972.

Boyden, Jo, Catherine Porter, and Ina Zharkevich. 2021. "Balancing school and work with new opportunities: changes in children's gendered time use in Ethiopia (2006–2013)." *Children's Geographies* 19 (1): 74–87. https://doi.org/10.1080/14733285.2020.1747600.

Bozick, Robert. 2007. "Making it through the first year of college: The role of students' economic resources, employment, and living arrangements." *Sociology of Education* 80 (3). https://doi.org/10.1177/003804070708000304.

Briones, Kristine. 2018. *A Guide to Young Lives Rounds 1 to 5 Constructed Files.* Technical Note 48. Oxford, United Kingdom: Young Lives, University of Oxford. https://www.younglives.org.uk/publications.

Brumberg, Joan J. 1997. *The body project.* Random House.

Bühler, Dorothee, Rasadhika Sharma, and Wiebke Stein. 2020. "Occupational Attainment and Earnings in Southeast Asia: The Role of Non-cognitive Skills." *Labour Economics* 67:101913. ISSN: 0927-5371. https://doi.org/https://doi.org/10.1016/j.labeco.2020.101913.

Burns, Tracey, and Francesca Gottschalk. 2019. *Educating 21st Century children: Emotional well-being in the digital Age.* Paris: OECD Publishing. https://doi.org/10.1787/b7f33425-en.

Burston, Mary A. 2017. "I work and don't have time for that theory stuff: time poverty and higher education*." *Journal of Further and Higher Education* 41 (4): 516–529. https://doi.org/10.1080/0309877X.2015.1135885.

Buscha, Franz, Arnaud Maurel, Lionel Page, and Stefan Speckesser. 2012. "The effect of employment while in high school on educational attainment: a conditional difference-in-differences approach." *Oxford Bulletin of Economics and Statistics* 74 (3). https://doi.org/10.1111/j.1468-0084.2011.00650.x.

Butler, Adam B., Kama D. Dodge, and Eric J. Faurote. 2010. "College student employment and drinking: A daily study of work stressors, alcohol expectancies, and alcohol consumption." *Journal of Occupational Health Psychology* 15 (3): 291–303. https://doi.org/10.1037\%2Fa0019822.

Caetano, Carolina, Gregorio Caetano, and Eric Nielsen. 2024. "Are children spending too much time on enrichment activities?" *Economics of Education Review* 98:102503. ISSN: 0272-7757. https://doi.org/doi.org/10.1016/j.econedurev.2023.102503. https://www.sciencedirect.com/science/article/pii/S0272775723001504.

Caetano, Gregorio, Josh Kinsler, and Hao Teng. 2019. "Towards causal estimates of children's time allocation on skill development." *Journal of Applied Econometrics* 34 (4): 588–605. https://doi.org/10.1002/jae.2700.

Caliendo, Marco, Deborah Cobb-Clark, and Arne Uhlendorff. 2010. *Locus of control and job search strategies.* IZA Discussion Paper 4750. Bonn, Germany: Institute of Labor Economics. https://doi.org/10.2139/ssrn.1552684.

Callender, Claire. 2008. "The impact of term-time employment on higher education students' academic attainment and achievement." *Journal of Education Policy* 23 (4). https://doi.org/10.1080/02680930801924490.

Campos-Vazquez, Raymundo M. 2018. "Returns to cognitive and non-cognitive skills: evidence for Mexico." *Applied Economics Letters* 25 (16): 1153–1156. https://doi.org/10.1080/13504851.2017.1403551.

Card, David. 2001. "Estimating the return to schooling: Progress on some persistent econometric problems." *Econometrica* 69 (5): 1127–1160. https://doi.org/10.1111/1468-0262.00237.

Casillas, A, J Way, and J Burrus. 2015. "Behavioral skills." In *Beyond academics: A holistic framework for enhancing education and workplace success,* edited by R. O'Connor, K. Mattern, and M. A. Hanson, 25–38. ACT.

Cech, Erin A. 2013. "The Self-Expressive Edge of Occupational Sex Segregation." *American Journal of Sociology* 119 (3): 747–789. https://doi.org/10.1086/673969.

Chadi, Adrian, and Manuel Hoffman. 2021. *Television, health, and happiness: A natural experiment in West Germany.* IZA Discussion Paper Series 14721. Institution of Labor Economics. Bonn, Germany: Institute of Labor Economics.

Chandra-Mouli, Venkatraman, Marina Plesons, and Avni Amin. 2018. "Addressing harmful and unequal gender norms in early adolescence." *Nature Human Behaviour* 2:239–240. https://doi.org/10.1038/s41562-018-0318-3.

Chang, Grace. 2022. "How is adolescents' time allocation associated with their self-Esteem and self-Efficacy? Evidence from four developing countries." *The Journal of Development Studies* 0 (0): 1–26. https://doi.org/10.1080/00220388.2022.2075735.

———. 2023. "How is university students' paid work associated with their locus of control?" *Research in Social Stratification and Mobility* 83:100764. ISSN: 0276-5624. https://doi.org/https://doi.org/10.1016/j.rssm.2023.100764. https://www.sciencedirect.com/science/article/pii/S0276562423000082.

Charles, Maria, and Karen Bradley. 2009. "Indulging Our Gendered Selves? Sex Segregation by Field of Study in 44 Countries." *American Journal of Sociology* 114 (4): 924–976. ISSN: 00029602, 15375390. http://www.jstor.org/stable/10.1086/595942.

Chen, Gilad, Stanley M. Gully, and Dov Eden. 2004. "General self-efficacy and self-esteem: toward theoretical and empirical distinction between correlated self-evaluations." *Journal of Organizational Behavior* 25 (3): 375–395. https://doi.org/10.1002/job.251.

Clark, Lee A., and David Watson. 1995. "Constructing validity: Basic issues in objective scale development." *Psychological Assessment* 7 (3): 309–319. https://doi.org/10.1037/1040-3590.7.3.309.

Clarke, Damian, Joseph P. Romano, and Michael Wolf. 2020. "The Romano-Wolf multiple hypothesis correction in Stata." *Stata Journal* 20 (4): 812–843. https://doi.org/10.1177/1536867X20976314.

Cobb-Clark, Deborah A. 2015. "Locus of control and the labor market." *IZA Journal of Labour Economics* 4 (3). https://doi.org/10.1186/s40172-014-0017-x.

Coyne, Sarah M., Adam A. Rogers, Jessica D. Zurcher, Laura Stockdale, and McCall Booth. 2020. "Does time spent using social media impact mental health?: An eight year longitudinal study." *Computers in Human Behavior* 104:106160. ISSN: 0747-5632. https://doi.org/10.1016/j.chb.2019.106160.

Crone, Eveline A., and Elly A. Konjin. 2018. "Media use and brain development during adolescence." *Nature Communications,* no. 588, https://doi.org/doi.org/10.1038/s41467-018-03126-x.

Crosnoe, Robert, and Monica K. Johnson. 2011. "Research on adolescence in the twenty-first century." *Annual Review of Sociology* 37 (1): 439–460. https://doi.org/10.1146/annurev-soc-081309-150008.

Cunha, Flavio, and James J. Heckman. 2008. "Formulating, identifying and estimating the technology of cognitive and noncognitive Skill formation." *Journal of Human Resources* 43 (4): 738–782. https://doi.org/10.3368/jhr.43.4.738.

Cunha, Flavio, James J. Heckman, Lance Lochner, and Dimitriy V. Masterov. 2006. "Interpreting the evidence on life cycle skill formation." Chap. 12 in *Handbook of the Economics of Education,* edited by Eric Hanushek and Finis Welch, 1:697–812. Elsevier. https://doi.org//10.1016/S1574-0692(06)01012-9.

Cunnien, Keith A, Nicole Martin Rogers, and Jeylan T Mortimer. 2009. "Adolescent work experience and self-efficacy." *International Journal of Sociology and Social Policy* 29 (3/4): 164–175. https://doi.org/10.1108/01443330910947534.

Cunningham, Wendy, Mònica P. Torrado, and Miguel Sarzosa. 2016. *Cognitive and non-cognitive Skills for The Peruvian labor market: Addressing measurement error through latent skills estimations.* Policy Research Working Paper 7550. Washington, DC: The World Bank.

Currie, Janet. 2020. “Child health as human capital.” *Health Economics* 29 (4): 452–463. https://doi.org/10.1002/hec.3995.

Cussianovich, Alexandra, and Vanessa Rojas. 2014. “The role of formal education in the subjective well-being of young teenagers in rural and urban Peru.” Chap. 7 in *Growing Up in Poverty,* edited by J. Boyden and M. Bourdillon, 161–179. London: Palgrave Studies on Children / Development. Palgrave Macmillan. https://doi.org/10.1057/9781137404039_8.

Dafoe, Allan. 2018. “Nonparametric identification of causal effects under temporal dependence.” *Sociological Methods & Research* 47 (2): 136–168. https://doi.org/10.1177/004912411561:784.

Dahl, Ronald E., Nicholas B. Allen, Linda Wilbrecht, and Ahna B. Suleiman. 2018. “Importance of investing in adolescence from a developmental science perspective.” *Nature* 554 (7693): 441–450. https://doi.org/10.1038/nature25770.

Dang, Hai-Anh H., and Paul W. Glewwe. 2017. “Well Begun, But Aiming Higher: A Review of Vietnam’s Education Trends in the Past 20 Years and Emerging Challenges.” *The Journal of Development Studies* 54 (7): 1171–1195. https://doi.org/10.1080/00220388.2017.1380797.

Danon, Alice Madeleine, Jishnu Das, Andreas De Barros, and Deon P. Filmer. 2023. *Cognitive and socioemotional skills in low-income countries.* Policy Research Working Paper 10309. The World Bank.

Darolia, Rajeev. 2014. “Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and part-time students.” *Economics of Education Review* 38 (C): 38–50. https://doi.org/10.1016/j.econedurev.2013.

Deci, Edward L., and Richard M. Ryan. 2008. “Hedonia, eudaimonia, and well-being: An introduction.” *Journal of Happiness Studies* 9:1–11. https://doi.org/10.1007/s10902-006-9018-1.

Del Boca, Daniela, Chiara Monfardini, and Cheti Nicoletti. 2017. "Parental and child time investments and the cognitive development of adolescents." *Journal of Labor Economics* 35 (2): 565–608. https://doi.org/10.1086/689479.

Del Bono, Emilia, Marco Francesconi, Yvonne Kelly, and Amanda Sacker. 2016. "Early Maternal Time Investment and Early Child Outcomes." *The Economic Journal* 126 (596): F96–F135. https://doi.org/10.1111/ecoj.12342.

Del Bono, Emilia, Josh Kinsler, and Ronni Pavan. 2020. *Skill formation and the trouble with child non-cognitive skill measures.* IZA Discussion Paper 13713. Bonn, Germany: Institute of Labor Economics. https://www.iza.org/publications/dp/13713/skill-formation-and-the-trouble-with-child-non-cognitive-skill-measures.

Dercon, Stefan, and Abhijeet Singh. 2013. "From Nutrition to Aspirations and Self-efficacy: Gender Bias over Time among Children in Four Countries." *World Development* 41:31–50.

Diaz, Juan J., Omar Arias, and David V. Tudela. 2013. "Does Perseverance Pay as Much as Being Smart?: The Returns to Cognitive and Non-cognitive Skills in urban Peru." Presented at IZA conference. http://conference.iza.org/conference_files/worldb2014/arias_o4854.pdf.

Dickson, Kelly, Michelle Richardson, Irene Kwan, Wendy MacDowall, Helen Burchett, Claire Stansfield, G. Brunton, Katy Sutcliffe, and James Thomas. 2018. *Screen-based activities and children and young people's mental health: A Systematic Map of Reviews.* Technical report. London: EPPI-Centre, Social Science Research Unit: UCL Institute of Education, University College London.

Diener, Ed, and Micaela Y. Chan. 2011. "Happy people live longer: Subjective wellbeing contributes to health and longevity." *Applied Psychological Health Well Being* 31 (1): 1–43. https://doi.org/10.1111/j.1758-0854.2010.01045.x.

Diener, Ed, Richard E. Lucas, Ulrich Schimmack, and John F. Helliwell. 2009. "Defining Well-Being." Chap. 2 in *Well-Being for Public Policy,* 8–20. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195334074.001.0001.

Dolan, Paul, Tessa Peasgood, and Matthew White. 2008. "Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective wellbeing." *Journal of Economic Psychology* 29 (1): 94–122. https://doi.org/10.1016/j.joep.2007.09.001.

Duckworth, Angela L, and David Scott Yaeger. 2015. "Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes." *Educational Researcher* 44 (4). https://doi.org/10.3102/0013189X15584327.

Dumas, Christelle. 2012. "Does work impede child learning? The case of Senegal." *Economic Development and Cultural Change* 60 (4): 773–93.

Dundes, Lauren, and Jeff Marx. 2006. "Balancing work and academics in college: Why do students working 10–19 hours per week excel?" *Journal of College Student Retention* 8 (1): 107–120. https://doi.org/10.2190/7UCU-8F9M-94QG-5WWQ.

Dweck, C. S. 2017. "From needs to goals and representations: Foundations for a unified theory of motivation, personality, and development." *Psychological Review* 246 (6). https://doi.org/10.1037/rev0000082.

Edmonds, Eric. 2008. "Child labor." Chap. 57 in *Handbook of Development Economics,* 1st ed., edited by T. Paul Schultz and John A. Strauss, 4:3607–3709. Elsevier.

Elkins, Rosemary K., Sonja C. Kassenboehmer, and Stefanie Schurer. 2017. "The stability of personality traits in adolescence and young adulthood." *Journal of Economic Psychology* 60 (1): 37–52. https://doi.org/10.1016/j.joep.2016.12.005.

Elkins, Rosemary K., and Stefanie Schurer. 2018. *Exploring the role of fathers in non-cognitive skill development over the lifecourse.* Working Papers, 2018-034. Human Capital and Economic Opportunity Working Group. https://ideas.repec.org/p/hka/wpaper/2018-034.html.

Ellis, Bruce J., Marco Del Giudice, Thomas J. Dishion, Aurealio J. Figueredo, Peter Gray, Vladas Griskevicius, Patricia H. Hawley, et al. 2012. “The evolutionary basis of risky adolescent behavior: Implications for science, policy, and practice.” *Developmental psychology* 48 (3): 598–623. https://doi.org/10.1037/a0026220.

Emerson, Patrick M., Vladimir Ponczek, and André P. Souza. 2017. “Child labor and learning.” *Economic Development and Cultural Change* 65 (2): 265–296. https://doi.org/10.1086/688895.

Escobal, Javier, and Eva Flores. 2008. *An assessment of the Young Lives sampling approach in Peru.* Technical Note 3. Oxford, United Kingdom: Young Lives, University of Oxford.

Espinoza-Revollo, Patricia, and Catherine Porter. 2018. *Evolving time use of children growing Up in Ethiopia, India, Peru and Vietnam, 2006-2016.* Working Paper 180. Oxford, United Kingdom: Young Lives, University of Oxford.

Evans, Emma, Keith Hawton, and Karen Rodham. 2004. “Factors associated with suicidal phenomena in adolescents: A systematic review of population-based studies.” *Clinical Psychology Review* 24 (8): 957–979. ISSN: 0272-7358. https://doi.org/10.1016/j.cpr.2004.04.005.

Favara, Marta, Grace Chang, and Alan Sánchez. 2018. *No longer children: What do Young Lives children do when they grow up? Transitions to post-secondary education and the labour market.* Research Report. Oxford, United Kingdom: Young Lives, University of Oxford.

Feldman, S. Shirley, and Glen R. Elliott. 1990. *At the threshold: the developing adolescent.* Cambridge, Mass: Harvard University Press. ISBN: 0674050355.

Ferguson, Christopher J. 2015. “Do angry birds make for angry children? A meta-analysis of video game influences on children’s and adolescents’ aggression, mental health, prosocial behavior, and academic performance.” *Perspectives on Psychological Science* 10 (5): 646–666. https://doi.org/10.1177/1745691615592234.

Festinger, Leon. 1954. "A theory of social comparison processes." *Human Relations* 7 (2): 117–140. https://doi.org/10.1177/001872675400700202.

Fiorini, Mario, and Michael Keane. 2014. "How the allocation of children's time affects cognitive and noncognitive development." *Journal of Labor Economics* 32 (4): 787–836. https://doi.org/10.1086/677232.

Ford, J., David Bosworth, and Robert A. Wilson. 1995. "Part-time work and full-time higher education." *Studies in Higher Education* 20 (2): 187–202. https://doi.org/10.1080/03075079512331381693.

Francesconi, Marco, and James J. Heckman. 2016. "Child development and parental investment: Introduction." *The Economic Journal* 126:F1–F27. https://doi.org/10.1111/ecoj.12388.

Gao, Wenjuan, Yunfeng Luo, Xiaojie Cao, and Xinqiao Liu. 2022. "Gender differences in the relationship between self-esteem and depression among college students: A cross-lagged study from China." *Journal of Research in Personality* 97:104202. ISSN: 0092-6566. https://doi.org/10.1016/j.jrp.2022.104202.

Geel, Regula, and Uschi Backes-Gellner. 2012. "Earning while learning: When and how student employment is beneficial." *Labour* 26 (3): 313–340. https://doi.org/10.1111/j.1467-9914.2012.00548.x.

Ghai, Sakshi, Luisa Fassi, Faisal Awadh, and Amy Orben. 2021. *Lack of sample diversity in research on adolescent depression and social media use: A scoping review and meta-analysis.* Pre-print. https://doi.org/10.31234/osf.io/s7juz. https://psyarxiv.com/s7juz/.

Gilchrist, Jenna D., Kate Battista, Karen A. Patte, Guy Faulkner, Valerie Carson, and Scott T. Leatherdale. 2021. "Effects of reallocating physical activity, sedentary behaviors, and sleep on mental health in adolescents." *Mental Health and Physical Activity* 20:100380. ISSN: 1755-2966. https://doi.org/10.1016/j.mhpa.2020.100380.

Ginsburg, Kenneth. 2007. "The importance of play in promoting healthy child development and maintaining strong parent-child bonds." *Pediatrics* 119:182–91. https://doi.org/10.1542/peds.2006-2697.

Goffman, Erving. 1977. "The Arrangement between the Sexes." *Theory and Society* 4 (3): 301–331. ISSN: 03042421, 15737853, accessed February 24, 2024. http://www.jstor.org/stable/656722.

Goldin, Claudia. 2006. "The quiet revolution that transformed women's employment, education, and family." *American Economic Review* 96 (2): 1–21. https://doi.org/10.1257/000282806777212350.

Goodman, Anna, Donna L. Lamping, and George B Ploubidis. 2010. "When to use broader internalising and externalising subscales instead of the hypothesised five subscales on the Strengths and Difficulties Questionnaire (SDQ): Data from British parents, teachers and children." *Journal of Abnormal Child Psychology* 38 (8): 1179–1191. https://doi.org/10.1007/s10802-010-9434-x.

Goodman, R, T Ford, H Simmons, R Gatward, and H Meltzer. 2000. "Using the Strengths and Difficulties Questionnaire (SDQ) to screen for child psychiatric disorders in a community sample." 177 (0): 534–539. https://doi.org/10.1192/bjp.177.6.534.

Goodman, Robert. 1997. "The Strengths and Difficulties Questionnaire: A research note." *Journal of Child Psychology and Psychiatry,* no. 38, 581–586. https://doi.org/10.1111/j.1469-7610.1997.tb01545.x.

Gottshalk, Peter. 2005. "Can work alter welfare recipients' beliefs?" *Journal of Policy Analysis and Management* 24 (3). https://doi.org/doi:10.1002/pam.20111.

Gracia, Pablo, Melissa Bohnert, and Seyma Celik. 2023. "Digital inequalities and adolescent mental health: the role of socioeconomic background, gender, and national context." In *Research Handbook on Digital Sociology,* 328–347. Edward Elgar Publishing.

Gracia, Pablo, Joan Garcia-Roman, Tomi Oinas, and Timo Anttila. 2020. "Child and Adolescent Time Use: A Cross-National Study." *Journal of Marriage and Family* 82 (4): 1304–1325. https://doi.org/https://doi.org/10.1111/jomf.12626. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jomf.12626. https://onlinelibrary.wiley.com/doi/abs/10.1111/jomf.12626.

———. 2022. "Gender differences in child and adolescent daily activities: A cross-national time use study." *Acta Sociologica* 65 (1): 41–65. https://doi.org/10.1177/00016993211008500.

Granic, Isabela, Adam Lobel, and Rutger C. M. E. Engels. 2014. "The benefits of playing video games." *American Psychologist* 69 (1): 66–78. https://doi.org/10.1037/a0034857.

Greenhaus, Jeffrey H., and Gary N. Powell. 2006. "When Work and Family Are Allies: A Theory of Work-Family Enrichment." *The Academy of Management Review* 31 (1): 72–92. ISSN: 03637425, accessed February 24, 2024. http://www.jstor.org/stable/20159186.

Grondin, Simon. 2010. "Timing and time perception: A review of recent behavioural and neuroscience findings and theoretical directions." *Attention, Perception, & Psychophysics* 72 (3): 561–582. https://doi.org/10.3758/APP.72.3.561.

Gruijters, Rob J., Isabel J. Raabe, and Nicolas Hübner. 2023. "Socio-emotional Skills and the Socioeconomic Achievement Gap." *Sociology of Education* 0 (0). https://doi.org/10.1177/00380407231216424.

Gugliemi, Silvia, Eric Neumeister, and Nicola Jones. 2021. *Adolescents, youth and the SDGs: What can we learn from the current data?* Technical report. United Kingdom: Gender and Adolescence: Global Evidence. https://www.gage.odi.org/wp-content/uploads/2021/09/Adolescents-youth-and-the-SDGs-what-can-we-learn-from-the-current-data.pdf.

Gunnarsson, Victoria, Peter Orazem, and Mario A. Sánchez. 2006. "Child labor and school achievement in Latin America." *World Bank Economic Review* 20 (1): 31–54. http://www.jstor.org/stable/40282318..

Hargittai, Eszter. 2008. "The Digital Reproduction of Inequality." In *Social Stratification: Class, Race and Gender in Sociological Perspective,* edited by David Grusky, 936–944. Co Westview Press.

Harter, Susan. 1993. "Self-Esteem: The Puzzle of Low Self-Regard (pp. 87-116)." *New York: Plenum Press. Herz, L., & GuIIone, E.(1999). The relationship between self-esteem and parenting style. Journal of Cross-Cultural Psychology* 30:742–762.

———. 2006. "The Development of Self-Esteem." In *Self-esteem issues and answers: A sourcebook of current perspectives,* edited by M. H. Kernis, 144–150. Psychology Press.

Hazell, Matthew, Emma Thornton, Hassan Haghparast-Bidgoli, and Praveetha Patalay. 2022. "Socio-economic inequalities in adolescent mental health in the UK: Multiple socio-economic indicators and reporter effects." *SSM - Mental Health* 2:100176. ISSN: 2666-5603. https://doi.org/10.1016/j.ssmmh.2022.100176.

Heckman, James, Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes." *American Economic Review* 103 (6): 2052–86. https://doi.org/10.1257/aer.103.6.2052. https://www.aeaweb.org/articles?id=10.1257/aer.103.6.2052.

Heckman, James J., T. Jagelka, and Tim Kautz. 2021. "Some contributions of economics to the study of personality." In *Handbook of personality: Theory and research,* edited by O. John and R. Robins, 853–892. New York: The Guilford Press. https://doi.org/10.7208/chicago/9780226100128.003.0009.

Heckman, James J., and Tim Kautz. 2013. "Fostering and measuring skills: Interventions that improve character and cognition." Chap. 5 in *The myth of achievement tests: The GED and the role of character in American Life,* edited by James J. Heckman, John E. Humphries, and Tim Kautz, 1. Chicago: University of Chicago Press. https://doi.org/10.7208/chicago/9780226100128.003.0009.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior." *Journal of Labor Economics* 24 (3): 411–482. https://doi.org/10.1086/504455.

Heineck, Guido, and Silke Anger. 2010. "The returns to cognitive abilities and personality traits in Germany." *Labour Economics* 17 (3): 535–546. ISSN: 0927-5371. https://doi.org/10.1016/j.labeco.2009.06.001.

Helsper, Ellen. 2021. *The digital disconnect: the social causes and consequences of digital inequalities.* SAGE.

Henrich, Joseph, Steven J Heine, and Ara Norenzayan. 2010. "The weirdest people in the world?" *Behavioural Brain Science* 33 (2-3): 83–135. https://doi.org/10.1017/s0140525x0999152x.

Hernández-Alava, Mónica, and Gurleen Popli. 2017. "Children's development and parental input: Evidence from the UK Millennium Cohort Study." *Demography* 54 (2): 485–511. https://doi.org/10.1007/s13524-017-0554-6.

Hervé, Justine, Subha Mani, Jere R Behrman, Arindam Nandi, Anjana Sankhil Lamkang, and Ramanan Laxminarayan. 2021. *Gender gaps in cognitive and noncognitive skills: roles of SES and gender attitudes.* PIER Working paper. https://doi.org/10.2139/ssrn.3788115. https://ssrn.com/abstract=3788115.

Hicks, Stephen, Lucy Tinkler, and Paul Allin. 2013. "Measuring subjective well-being and its potential role in policy: Perspectives from the UK Office for National Statistics." *Social Indicators Research* 114 (1): 73–86. https://doi.org/10.1007/s11205-013-0384-x.

Hisler, Garrett, Jean M. Twenge, and Zlatan Krizan. 2020. "Associations between screen time and short sleep duration among adolescents varies by media type: Evidence from a cohort study." *Sleep Medicine* 66:92–102. https://doi.org/10.1016/j.sleep.2019.08.007.

Hitlin, Steven, and Mmonica K Johnson. n.d. "Reconceptualizing Agency within the Life Course: The Power of Looking Ahead." *American journal of sociology* 120 (5): 1429–1472. https://doi.org/10.1086/681216.

Hoare, Erin, Karen Milton, Charlie Foster, and Steven Allender. 2016. "The associations between sedentary behaviour and mental health among adolescents: A systematic review." *International Journal of Behavioral Nutrition* 13 (108). https://doi.org/10.1186/s12966-016-0432-4.

Holford, Angus. 2020. "Youth employment, academic performance and labour market outcomes: Production functions and policy effects." *Labour Economics* 63:101806. ISSN: 0927-5371. https://doi.org/10.1016/j.labeco.2020.101806. https://www.sciencedirect.com/science/article/pii/S0927537120300129.

Hook, Jennifer L. 2006. "Men's unpaid work in 20 countries, 1965-2003." *American Sociological Review* 71 (4): 639–660. https://doi.org/10.1177/000312240607100406.

Hossain, Mobarak, and Matthew C. H. Jukes. 2023. *Gender differences in socioemotional skills among adolescents and young adults in Ethiopia, India, Peru and Vietnam.* Research Report. Oxford, United Kingdom: Young Lives, University of Oxford. https://www.younglives.org.uk/sites/default/files/2023-07/YL-GenderDifferencesReport-Jun23%20Final.pdf.

House of Commons. 2019. *Impact of social media and screen-use on young people's health.* Fourteenth report of session 2017-19. House of Commons. https://publications.parliament.uk/pa/cm201719/cmselect/cmsctech/822/822.pdf.

Howieson, Cathy, Jim McKechnie, Sandy Hobbs, and Sheila Semple. 2012. "New perspectives on school students' part-time work." *Sociology* 46 (2): 322–338. https://doi.org/10.1177\%2F0038038511419183.

Hsin, Amy, and Christina Felfe. 2014. "When Does Time Matter? Maternal Employment, Children's Time With Parents, and Child Development." *Demography* 51 (5): 1867–1894. ISSN: 1533-7790. https://doi.org/10.1007/s13524-014-0334-5.

Hubble, Susan, and Paul Bolton. 2018. *Higher education tuition fees in England.* Briefing paper 8151. Accessed 28 May 2020. United Kingdom: House of Commons Library. https://commonslibrary.parliament.uk/research-briefings/cbp-8151.

Huebner, Scott. 1994. "Preliminary development and validation of a multidimensional life satisfaction scale for children." *Psychological Assessment* 6 (2): 149–158. https://doi.org/10.1037/1040-3590.6.2.149.

Humphrey, Robin. 2006. "Pulling structured inequality into higher education: The impact of part-time working on English university students." *Higher Education Quarterly* 60 (3).

Hunt, Eithne, and Elizabeth Anne McKay. 2015. "What can be learned from adolescent time diary research." *Journal of Adolescent Health* 56 (3): 259–266. https://doi.org/10.1016/j.jadohealth.2014.11.007.

Huppert, Felicia, Nic Marks, Andrew Clark, Johannes Siegrist, Alois Stutzer, Joar Vittersø, and Morten Wahrendorf. 2008. "Measuring Well-being Across Europe: Description of the ESS Well-being Module and Preliminary Findings." *Social Indicators Research* 91 (February). https://doi.org/10.1007/s11205-008-9346-0.

Huppert, Felicia A. 2009. "Psychological well-being: Evidence regarding its causes and consequences." *Applied Psychology: Health and Well-Being* 1 (2): 137–164. https://doi.org/10.1111/j.1758-0854.2009.01008.x.

Huppert, Felicia A., and Timothy T. C. So. 2013. "Flourishing Across Europe: Application of a New Conceptual Framework for Defining Well-Being." *Social indicators research* 110 (3): 837–861. https://doi.org/10.1007/s11205-011-9966-7.

ILO. 2017. *Global estimates of child labour: Results and trends, 2012-2016.* Report. Geneva: International Labour Office.

———. 2018a. *Care work and care jobs for the future of decent work.* Technical Report. International Labour Organization, Geneva. https://www.ilo.org/global/publications/books/WCMS_633135/lang--en/index.htm.

———. 2018b. *Child labour and the youth decent work deficit in Tanzania.* Technical Report. Geneva: International Labour Office, Fundamental Principles and Rights at Work Branch (FUNDAMENTALS).

———. 2021. *Child Labour: Global estimates 2020, trends and the road forward.* Report. Geneva: International Labour Office.

Johnston, David, Carol Propper, Stephen Pudney, and Michael Shields. 2014. "Child mental health and educational attainment: multiple observers and the measurement error problem." *Journal of Applied Econometrics* 29 (6): 880–900. https://doi.org/doi.org/10.1002/jae.2359. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/jae.2359.

Jürges, Hendrik, and Rasheda Khanam. 2021. "Adolescents' time allocation and skill production." *Economics of Education Review* 85, no. 1 (102178). https://doi.org/10.1016/j.econedurev.2021.102178.

Kalenkoski, Charlene M., and Sabrina W. Pabilonia. 2009. "Does working while in high school reduce US study time?" *Social Indicators Research* 93 (1). https://doi.org/10.1007/s11205-008-9412-7.

Kan, Man Yee, Oruek Sullivan, and Jonathan Gershuny. 2011. "Gender convergence in domestic work: Discerning the effects of interactional and instutitional barriers from large-scale data." *Sociology* 42 (2): 234–251. https://doi.org/10.1177/0038038510394014.

Kandola, Aaron, Borja del Pozo Cruz, Joseph F. Hayes, Neville Owen, David W. Dunstan, and Mats Hallgren. 2022. "Impact on adolescent mental health of replacing screen-use with exercise: A prospective cohort study." *Journal of Affective Disorders* 301:240–247. ISSN: 0165-0327. https://doi.org/doi.org/10.1016/j.jad.2021.12.064. https://www.sciencedirect.com/science/article/pii/S0165032721013847.

Kandola, Aaron, Gemma Lewis, David P. J. Osborn, Brendon Stubbs, and Joseph F. Hayes. 2020. "Depressive symptoms and objectively measured physical activity and sedentary behaviour throughout adolescence: A prospective cohort study." *Lancet Psychiatry* 7 (3): 262–271. https://doi.org/10.1016/S2215-0366(20)30034-1.

Kassenboehmer, Sonja C., Felix Leung, and Stefanie Schurer. 2018. "University education and non-cognitive skill development." *Oxford Economic Papers* 80 (2). https://doi.org/10.1093/oep/gpy002.

Kautz, Tim, James J. Heckman, Ron Diris, Bas ter Weel, and Lex Borghans. 2014. *Fostering and Measuring Skills: Improving Cognitive and Non-cognitive Skills to Promote Lifetime Success.* OECD Education Working Papers 110. OECD Publishing. https://doi.org/10.1787/5jxsr7vr78f7-en. https://ideas.repec.org/p/oec/eduaab/110-en.html.

Keane, Michael, Sonya Krutikova, and Timothy Neal. 2020. *The impact of child work on cognitive development: Results from four low to middle income countries.* IFS Working Paper W.20/36. Institute for Fiscal Studies, London, United Kingdom. https://doi.org/10.1920/wp.ifs.2018.2918.

Keele, Luke, and Nathan J. Kelly. 2006. "Dynamic models for dynamic theories: The ins and outs of lagged dependent variables." *Political Analysis* 14 (1): 186–205. https://doi.org/10.1093/pan/mpj006.

Kelly, Yvonne, Afshin Zilanawala, Cara Booker, and Amanda Sacker. 2019. "Social media use and adolescent mental health: Findings from the Millenium Cohort Study." *EClinicalMedicine* 6:59–68. https://doi.org/10.1016/j.eclinm.2018.12.005.

Kennewell, Eliza, Rachel G Curtis, Carol Maher, Samuel Luddy, and Rosa Virgara. 2022. "The relationships between school children's wellbeing, socio-economic disadvantage and after-school activities: a cross-sectional study." *BMC Pediatrics* 22 (297). https://doi.org/10.1186/s12887-022-03322-1.

Ketende, Sosthenes C., and Elizabeth M. Jones. 2011. *User Guide to Analysing MCS Data Using STATA.* User Guide. Retrieved from UK Data Service website. London, UK: Centre for Longitudinal Studies. https://doi.org/10.5255/UKDA-SN-8156-7.

Khanam, Rasheda, Son Nghiem, and Maisha Rahman. 2020. "The income gradient and child mental health in Australia: does it vary by assessors?" *The European Journal of Health Economics* 21:19–36.

Kling, K C, J S Hyde, C J Showers, and B N Buswell. 1999. "Gender differences in self esteem: a meta-analysis." *Psychological Bulletin* 125:470–500. https://doi.org/10.1037/0033-2909.125.4.470.

Kossek, Ellen Ernst, and Kyung-Hee Lee. 2017. *Work-Family Conflict and Work-Life Conflict,* October. https://doi.org/10.1093/acrefore/9780190224851.013.52.

Krauss, Samantha, and Ulrich Orth. 2022. "Work Experiences and Self-Esteem Development: A Meta-Analysis of Longitudinal Studies." *European Journal of Personality* 36 (6): 849–869. https://doi.org/10.1177/08902070211027142.

Krueger, Alan B., and Arthur A. Stone. 2014. "Measuring subjective wellbeing: Progress and challenges." *Science* 346 (6205): 42–43. https://doi.org/10.1126/science.1256392.

Kumra, Neha. 2009. *An assessment of the Young Lives sampling approach in Andhra Pradesh, India.* Technical note 2. Oxford, United Kingdom: Young Lives, University of Oxford.

Laajaj, Rachid, and Karen Macours. 2021. "Measuring skills in developing countries." *The Journal of Human Resources* 56 (4): 1254–1295. https://doi.org/10.3368/jhr.56.4.1018-9805R1.

Lacey, Rebecca E, Baowen Xue, and Anne McMunn. 2022. "The mental and physical health of young carers: a systematic review." *The Lancet Public Health* 7 (9): E787–E796. https://doi.org/10.1016/S2468-2667(22)00161-X.

Lamb, Sharon, and Julie Koven. 2019. "Sexualization of girls: Addressing criticism of the APA Report, presenting new evidence." *SAGE Open* 9 (4): 1–15. https://doi.org/10.1177/2158244019881024.

Layard, Richard, Carol Graham, Jan-Emanuel De Neve, and Gus O'Donnell. 2022. *A well-being manifesto.* https://cep.lse.ac.uk/textonly/people/layard/papers/0598_Wellbeing Manifesto.pdf.

Leary, Mark R. 2012. "Sociometer theory." In *Handbook of theories of social psychology,* 2nd edition, edited by Paul A M Van Lange, Arie W. Kruglanski, and E. Tory Higgins. Sage. https://doi.org/10.4135/9781446249222.n33.

Lefcourt, Herbert M. 1991. "Locus of control." In *Measures of personality and social psychology attitudes,* edited by J.P. Robinson, P. R. Shaver, and L.S. Wrightman, 413–425. Academic Press Ltd. https://doi.org/10.1016/B978-0-12-590241-0.50013-7.

Lenhart, Amanda. 2015a. *Teens, Social Media & Technology Overview 2015.* Washington, DC 20036. https://www.pewresearch.org/internet/2015/04/09/teens-social-media-technology-2015/.

———. 2015b. *Teens, Technology and Friendships. Video games, social media and mobile phones play an integral role in how teens meet and interact with friends.* Washington, DC 20036. https://www.pewresearch.org/internet/2015/08/06/teens-technology-and-friendships/U.

Lesner, Rune V., Anna P. Damm, Preben B. Bertelsen, and Mads U. Pedersen. 2018. *Life skills development of teenagers through spare-time jobs.* Working paper. Aarhus, Denmark: TrygFonden's Centre for Child Research. https://econ.au.dk/research/publications/economics-working-papers.

Leszczensky, Lars, and Tobias Wolbring. 2019. "How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study." *Sociological Methods & Research,* 1–29. https://doi.org/10.1177/0049124119882473.

Leung, Louis. 2014. “Predicting internet risks: A longitudinal panel study of gratifications-sought, internet addiction symptoms and social media use among children and adolescents.” *Health Psychology and Behavioral Medicine* 2 (1): 424–439.

Levy, Jessica K., Gary L. Dormstadt, Caitlin Ashby, Erika Halsey, Aishwarya Nagar, and Margaret E. Greene. 2020. “Characteristics of successful programmes targeting gender inequality and restrictive gender norms for the health and wellbeing of children, adolescents, and young adults: A systematic review.” *Lancet Global Health* 8 (2): E225–E236. https://doi.org/10.1016/S2214-109X(19)30495-4.

Livingstone, Sonia, Leslie Haddon, Anke Görzig, and Kjartan Ólafsson. 2011. *Risks and safety on the internet: the perspective of European children: full findings and policy implications from the EU Kids Online survey of 9-16 year olds and their parents in 25 countries.* EU Kids Online, Deliverable D4. EU Kids Online Network. http://eprints.lse.ac.uk/33731/.

Livingstone, Sonia, and Ellen Helsper. 2007. “Gradations in digital inclusion: children, young people and the digital divide.” *New Media & Society* 9 (4): 671–696. https://doi.org/10.1177/1461444807080335.

Livingstone, Sonia, Giovanna Mascheroni, Michael Dreier, Stephane Chaudron, and Kaat Lagae. 2015. *How parents of young children manage digital devices at home: The role of income, education and parental style.* Report. London: EU Kids Online: London School of Economics and Political Science. https://www.lse.ac.uk/media-and-communications/research/research-projects/eu-kids-online/reports-and-findings.

Livingstone, Sonia, Giovanna Mascheroni, and Elisabeth Staksrud. 2018. “European research on children’s internet use: Assessing the past and anticipating the future.” *New Media & Society* 20 (3): 1103–1122. https://doi.org/10.1177/1461444816685930.

Livingstone, Sonia, Anulekha Nandi, Shakuntala Banaji, and Mariya Stoilova. 2017. *Young adolescents and digital media: uses, risks and opportunities in low- and middle-income countries: a rapid evidence review.* Report. London: Gage. http://www.gage.odi.org/.

Lucas, Richard E., and Ed Diener. 2009. "Personality and subjective well-being." In *The science of well-being: The collected works of Ed Diener,* edited by Ed Diener, 75–102. Springer Science + Business Media. https://doi.org/10.1007/978-90-481-2350-6.

Luszczynska, Aleksandra, Benicio Gutiérrez-Doña, and Ralf Schwarzer. 2005. "General self-efficacy in various domains of human functioning: Evidence from five countries." *International Journal of Psychology* 40 (2): 80–89. https://doi.org/10.1080/00207590444000041.

Maggio, Paul Di, Eszter Hargittai, Coral Celeste, and Steven Shafer. 2004. "Digital inequality: From unequal access to differentiated use" [in English (US)]. In *Social Inequality,* 355–400. Russell Sage Foundation. ISBN: 0871546205.

Maher, Jo, Keeva Rooney, Mari Toomse-Smith, Zsolt Kiss, Emma Pollard, Matthew Williams, Jim Hillage, Martha Green, Clare Huxley, and Wil Hunt. 2018. *Student income and expenditure survey 2014 to 2015.* Technical report. United Kingdom: Department for Education. https://www.gov.uk/government/publications/student-income-and-expenditure-survey-2014-to-2015.

Marsh, Herbert W. 1991. "Employment during high school: Character building or a subversion of academic goals?" *Sociology of Education* 64 (3). https://doi.org/10.2307/2112850.

Matulevich, Rubiano, Eliana Carolina, and Mariana Viollaz. 2019. *Gender Differences in Time Use : Allocating Time between the Market and the Household (English).* Policy Research working paper WPS 8981. Retrieved from World Bank website. Washington, D.C.: World Bank Group. http://documents.worldbank.org/curated/en/555711565793045322/Gender-Differences-in-Time-Use-Allocating-Time-between-the-Market-and-the-Household.

Mcdool, Emily, Philip Powell, Jennifer Roberts, and Karl Taylor. 2020. "The internet and children's psychological wellbeing." *Journal of Health Economics* 69. https://doi.org/10.1016/j.jhealeco.2019.102274.

McNamee, Paul, Silvia Mendolia, and Oleg Yerokhin. 2021. "Social media use and emotional and behavioural outcomes in adolescence: Evidence from British longitudinal data." *Economics & Human Biology* 41. https://doi.org/10.1016/j.ehb.2021.100992.

McVicar, Duncan, and Brian McKee. 2002. "Part-time work during post-compulsory education and examination performance: help or hindrance?" *Scottish Journal of Political Economy* 49 (4). https://doi.org/10.1111/1467-9485.00238.

Melius, Janella. 2010. *Student engagement as a factor in academic achievement: The case study of undergraduates at Norfolk State University, Virginia.* Edwin Mellen Press.

Meroni, Elena C., Daniela Piazzalunga, and Chiara Pronzato. 2021. "Allocation of time and child socio-emotional skills." *Review of Economics of the Household,* https://doi.org/10.1007/s11150-021-09580-9.

Metcalf, Hilary. 2003. "Increasing inequality in higher education: the role of term-time working." *Oxford Review of Education* 29 (3): 315–329. https://doi.org/10.1080/03054980307447.

Mincer, Jacob. 1974. *Schooling, experience, and earnings.* New York: National Bureau of Economic Research. Distributed by Columbia University Press.

Mitchell, Mark, Marta Favara, Catherine Porter, and Alan Sánchez. 2023. "Human Capital Development. New evidence on the production of socio-emotional skills." *Journal of Human Resources,* ISSN: 0022-166X. https://doi.org/10.3368/jhr.1120-11342R1.

Mitrofan, Oana, Moli Paul, and Nicholas Spencer. 2009. "Is aggression in children with behavioural and emotional difficulties associated with television viewing and video game playing? A systematic review." *Child: Care, Health and Development* 35 (1): 5–15. https://doi.org/10.1111/j.1365-2214.2008.00912.x.

Mogonea, Florentin-Remus, and Florentina Mogonea. 2014. "The Role of the Family in Building Adolescents' Self-esteem." The International Conference PSYCHOLOGY AND THE REALITIES OF THE CONTEMPORARY WORLD – 4th EDITION - PSIWORLD 2013, *Procedia - Social and Behavioral Sciences* 127:189–193. ISSN: 1877-0428. https://doi.org/10.1016/j.sbspro.2014.03.238. https://www.sciencedirect.com/science/article/pii/S1877042814023295.

Morrow, Virginia, and Jo Boyden. 2018. *Responding to children's work: Evidence from the Young Lives study in Ethiopia, India, Peru and Vietnam.* Summative Report. Oxford, United Kingdom: Young Lives, University of Oxford. https://www.younglives.org.uk/publications.

Mortimer, Jeylan T. 2003. *Working and growing up in America.* US: Harvard University Press.

Mullan, Killian. 2018. "Technology and children's screen-based activities in the UK: The story of the millennium so far." *Child Indicators Research* 11:1874–8988. https://doi.org/10.1007/s12187-017-9509-0.

———. 2019. "A child's day: Trends in time use in the UK from 1975 to 2015." *The British Journal of Sociology* 70 (3): 998–1024. https://doi.org/10.1111/1468-4446.12369.

Nature. 2021. *Young people's mental health is finally getting the attention it needs.* Editorial. https://doi.org/10.1038/d41586-021-02690-5.

Neve, Jan-Emmanuel De, Ed Diener, Louis Tay, and Cody Xuereb. 2013. "The objective benefits of subjective well-being." In *World Happiness Report 2013,* edited by J Helliwell, R Layard, and J Sachs. New York, NY: UN Sustainable Development Solutions Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2306651.

Neves, Jonathan, and Jason Leman. 2019. *Postgraduate taught experience survey.* Advance HE. https://www.advance-he.ac.uk/reports-publications-and-resources/postgraduate-taught-experience-survey-ptes.

Newlove-Delgado, Tamsin, Tracy Williams, Katy Robertson, Sally McManus, Katharine Sadler, Tim Vizard, Cher Cartwright, et al. 2017. *Mental health of children and young people in England, 2021: Wave 2 follow up to the 2017 survey.* The National Archives, Kew, Richmond, Surrey, TW9 4DU.

Neyt, Brecht, Eddy Omey, Dieter Verhaest, and Stijn Baert. 2019. "Does student work really affect educational outcomes? A review of the literature." *The Journal of Economic Surveys* 33 (3). https://doi.org/10.1111/joes.12301.

Ngo, Hazel, Douglas P. VanderLaan, and Madison Aitken. 2020. "Self-esteem, symptom severity, and treatment response in adolescents with internalizing problems." *Journal of Affective Disorders* 273:183–191. ISSN: 0165-0327. https://doi.org/https://doi.org/10.1016/j.jad.2020.04.045. https://www.sciencedirect.com/science/article/pii/S0165032719327570.

Nguyen, Ha Trong, Sally Brinkman, Huong Thu Le, Stephen R. Zubrick, and Francis Mitrou. 2022. "Gender differences in time allocation contribute to differences in developmental outcomes in children and adolescents." *Economics of Education Review* 89 (102270). https://doi.org/10.1016/j.econedurev.2022.102270.

Nguyen, Ngoc P. 2008. *An assessment of the Young Lives sampling approach in Vietnam.* Young Lives Technical Note 4. Oxford, United Kingdom: Young Lives, University of Oxford.

Nieto, Adrián, and Marc Suhrcke. 2021. "The effect of TV viewing on children's obesity risk and mental well-being: Evidence from the UK digital switchover." *Journal of Health Economics* 80:102543. ISSN: 0167-6296. https://doi.org/10.1016/j.jhealeco.2021.102543.

Nonis, Sarath, and Gail Hudson. 2006. "Academic Performance of College Students: Influence of Time Spent Studying and Working." *The Journal of Education for Business* 81 (January): 151–159. https://doi.org/10.3200/JOEB.81.3.151-159.

Nunes, Filipa, Paula Mena Matos, Tiago Ferreira, Ingrid Schoon, and Catarina Pinheiro Mota. 2023. "Ecological correlates of adolescents' sense of agency: Are there differences for boys and girls?" *Personality and Individual Differences* 214:112354. ISSN: 0191-8869. https://doi.org/10.1016/j.paid.2023.112354. https://www.sciencedirect.com/science/article/pii/S0191886923002775.

O'Neill, Stephen, Noèmi Krief, Richard Grieve, Matthew Sutton, and Jasjeet S. Sekhon. 2016. "Estimating causal effects: considering three alternatives to difference-in-differences estimation." *Health Services and Outcomes Research Methodology* 16:1572–9400. https://doi.org/10.1007/s10742-016-0146-8.

OECD. 2017. *Youth well-being policy review of Viet Nam.* Report. EU-OECD Youth Inclusion Project, Paris. https://www.oecd.org/countries/vietnam/OECDYouthReportVietNam_ebook.pdf.

———. 2018. *PISA 2018 database.* data retrieved from OECD https://www.oecd.org/pisa/data/2018database/.

———. 2021. *Beyond Academic Learning: First Results from the Survey of Social and Emotional Skills.* OECD Publishing.

Ofcom. 2015. *Children and parents: Media use and attitudes report.* Report. Ofcom. ofcom.org.uk/__data/assets/pdf_file/0024/78513/childrens_parents_nov2015.pdf.

Olds, Timothy, Ben Singh, Aaron Miatke, Emily Eglitis, Carol Maher, and Dorothea Dumuid. 2023. "The Association Between Socioeconomic Status and Use of Time in Australian Children and Adolescents." *The Journal of adolescent health* 73 (6): 1068–1076. https://doi.org/10.1016/j.jadohealth.2023.07.007.

ONS. 2017. *Annual Population Survey, January - December, 2010.* 4th Edition. UK Data Service. SN: 6809. https://doi.org/10.5255/UKDA-SN-6809-4.

———. 2021. *Average actual weekly hours of work for part-time workers (seasonally adjusted).* Labour market statistics time series. Accessed on 20 October 2021. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/labourmarketstatistics.

Orben, Amy. 2020. "Teenagers, screens and social media: a narrative review of reviews and key studies." *Social Psychiatry and Psychiatric Epidemiology* 55:407–414. https://doi.org/10.1007/s00127-019-01825-4.

Orben, Amy, and Andrew K. Przybylski. 2019. "Screens, teens, and psychological well-being: Evidence from three time-use-diary studies." *Psychological Science* 30:682–696. https://doi.org/10.1038/s41562-018-0506-1.

———. 2020. "Teenage sleep and technology engagement across the week." *PeerJ* 8 (e8427). https://doi.org/10.7717/peerj.8427.

Outes-Leon, Ingo, and Alan Sanchez. 2008. *An Assessment of the Young Lives Sampling Approach in Ethiopia.* Young Lives Technical Note, 1. Young Lives, University of Oxford, Oxford, United Kingdom. https://www.younglives.org.uk/publications.

Painter II, M A. 2010. "Get a job and keep it! High school employment and adult wealth accumulation." *Research in Social Stratification and Mobility* 28 (1): 233–249. https://doi.org/10.1016/j.rssm.2010.01.006.

Pankhurst, Alula, Gina Crivello, and Agazi Tiumelissan. 2015. In *Children's Work and Labour in East Africa: Social Context and Implications for Policy,* edited by Alula Pankhurst, Michael Bourdillon, and Gina Crivello. PO Box 31971, Addis Ababa, Ethiopia: Addis Ababa: Organisation for Social Sicence Research in Eastern and Southern Africa (OSSREA). http://www.ossrea.net.

Passaretta, Giampiero, and Moris Triventi. 2015. "Work experience during higher education and post-graduation occupational outcomes: A comparative study on four European countries." *International Journal of Comparative Sociology* 56 (3-4): 232–253. https://doi.org/10.1177/0020715215587772.

Patton, George C., Susan M. Sawyer, John S. Santelli, David A. Ross, Rima Afifi, Nicholas B. Allen, Monika Arora, et al. 2016. "Our future: A Lancet commission on adolescent health and wellbeing." *The Lancet* 387 (10036): P2423–2478. https://doi.org/10.1016/S0140-6736(16)00579-1.

Pei, Zhuan, Jörn-Steffen Pischke, and Hannes Schwandt. 2019. "Poorly measured confounders are more useful on the left than on the right." *Journal of Business & Economic Statistics* 37 (2): 205–216. https://doi.org/10.1080/07350015.2018.1462710.

Peng, Biao, Ningning Hu, Huiying Yu, Hanshi Xiao, and Jie Luo. 2021. "Parenting Style and Adolescent Mental Health: The Chain Mediating Effects of Self-Esteem and Psychological Inflexibility." *Frontiers in Psychology* 12 (738170). https://doi.org/10.3389/fpsyg.2021.738170.

Petot, Djaouida, Leslie Rescorla, and Jean-Michel Petot. 2011. "Agreement between parent- and self-reports of Algerian adolescents' behavioral and emotional problems." *Journal of adolescence* 34 (5): 977–986.

Pfeifer, Jennifer H., and Nicholas B. Allen. 2021. "Puberty Initiates Cascading Relationships Between Neurodevelopmental, Social, and Internalizing Processes Across Adolescence." Adolescent Brain Development and Psychopathology, *Biological Psychiatry* 89 (2): 99–108. ISSN: 0006-3223. https://doi.org/https://doi.org/10.1016/j.biopsych.2020.09.002. https://www.sciencedirect.com/science/article/pii/S0006322320319053.

Piatek, Rémi, and Pia Pinger. 2016. "Maintaining (locus of) control? Data combination for the identification and inference of factor structure models." *Journal of Applied Economics* 31. https://doi.org/10.1002/jae.2456.

Proctor, Carmel L., Roger Tweed, and Daniel Morris. 2015. "The naturally emerging structure of well-being among young adults: "Big Two" or other framework?" *Journal of Happiness Studies* 16:257–275. https://doi.org/10.1007/s10902-014-9507-6.

Przybylski, Andrew K., and Netta Weinstein. 2017. "A large-scale test of the Goldilocks Hypothesis: Quantifying the relations between digital-screen use and the mental well-being of adolescents." *Psychological Science* 28 (2): 204–215. https://doi.org/10.1177/0956797616678438.

———. 2019. "Violent video game engagement is not associated with adolescents' aggressive behaviour: evidence from a registered report." *Royal Society Open Science* 6 (2): 171474. https://doi.org/10.1098/rsos.171474.

Putnick, Diane L., and Marc H. Bornstein. 2015. "Is child labor a barrier to school enrollment in low- and middle-income countries?" *International Journal of Educational Development* 41 (C): 112–120. https://doi.org/10.1016/j.ijedudev.2015.02.001.

Puukko, Kati, Lauri Hietajärvi, Erika Maksniemi, Kimmo Alho, and Katariina Salmela-Aro. 2020. "Social media use and depressive symptoms – A longitudinal study from early to late adolescence." *International Journal of Environmental Research and Public Health* 17 (5921). https://doi.org/10.3390/ijerph17165921.

Al-Qaisy, Lama M. 2011. "The relation of depression and anxiety in academic achievement among group of university students." *Int J Psychol Couns* 3 (5): 96–100.

Quadlin, Natasha. 2020. "From major preferences to major choices: Gender and logics of major choice." *Sociology of Education* 93 (2): 91–109. https://doi.org/10.1177/0038040719887971.

Quintini, Glenda. 2015. *Working and learning: A diversity of patterns.* OECD Social, Employment and Migration Working Papers 169. Paris, France. https://doi.org/10.1787/5jrw4bz6hl43-en.

Ragnedda, Massimo. 2018. "Conceptualizing digital capital." *Telematics and Informatics* 35 (8): 2366–2375. ISSN: 0736-5853. https://doi.org/https://doi.org/10.1016/j.tele.2018.10.006. https://www.sciencedirect.com/science/article/pii/S0736585318309316.

Rees, Gwyther. 2017. "Children's activities and time use: Variations between and within 16 countries." Children's Well-being around the world: Findings from the Children's Worlds (ISCWeB) project, *Children and Youth Services Review* 80:78–87. ISSN: 0190-7409. https://doi.org/10.1016/j.childyouth.2017.06.057.

Rescorla, Leslie A, Sofia Ginzburg, Thomas M Achenbach, Masha Y Ivanova, Fredrik Almqvist, Ivan Begovac, Niels Bilenberg, Hector Bird, Myriam Chahed, Anca Dobrean, et al. 2013. "Cross-informant agreement between parent-reported and adolescent self-reported problems in 25 societies." *Journal of Clinical Child & Adolescent Psychology* 42 (2): 262–273.

Roberts, Brent W., Nathan R. Kuneel, Rebecca Shiner, Avshalom Caspi, and Lewis R. Goldberg. 2008. "The power of personality. The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes." *Perspectives on Psychological Science* 2 (4): 313–345. https://doi.org/10.1111/j.1745-6916.2007.00047.x.

Robotham, David. 2008. "Stress among higher education students: Towards a research agenda." *Higher Education* 56. https://doi.org/10.1007/s10734-008-9137-1.

Roest, Jennifer. 2016. *Child Marriage and Early Child-bearing in India: Risk Factors and Policy Implications.* Policy Paper 10. Oxford, United Kingdom: Young Lives, University of Oxford.

Rogoff, Barbara. 2003. *The cultural nature of human development.* Oxford University Press. ISBN: 9780195131338.

Rosenberg, Morris. 1965. *Society and the Adolescent Self-Image.* Princeton University Press. ISBN: 9780691093352. https://doi.org/10.1126/science.148.3671.804.

Ross, David A., Rachel Hinton, Meheret Melles-Brewer, Danielle Engel, Willibald Zeck, Lucy Fagan, Joanna Herat, et al. 2020. "Adolescent well-being: A definition and conceptual framework." *The Journal of Adolescent Health* 67 (4): 472–476. https://doi.org/10.1016/j.jadohealth.2020.06.042.

Rothstein, Donna S. 2007. “High school employment and youths’ academic achievement.” *Journal of Human Resources* 42 (1). https://doi.org/doi:10.3368/jhr.XLII.1.194.

Ryan, Richard M., and Edward L. Deci. 2017. *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness.* Guilford Press. https://doi.org/10.1521/978.14625/28806.

Ryan, Richard M., Bart Soenens, and Maarten Vansteenkiste. 2019. “Reflections on self-determination theory as an organizing framework for personality psychology: Interfaces, integrations, issues, and unfinished business.” *Journal of Personality* 87 (1): 115–145. https://doi.org/10.1111/jopy.12440. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jopy.12440. https://onlinelibrary.wiley.com/doi/abs/10.1111/jopy.12440.

Sadler, Katharine, Tim Vizard, Tamsin Ford, Franziska Marcheselli, Nicola Pearce, Dhriti Mandalia, Jodie Davis, et al. 2017. *Mental health of children and young people in England, 2017.* The National Archives, Kew, Richmond, Surrey, TW9 4DU.

Sánchez, Alan, and Javier Escobal. 2020. “Survey attrition after 15 years of tracking children in four developing countries: The Young Lives study.” *Review of Development Economics* 24 (1): 1196–1216. https://doi.org/https://doi.org/10.1111/rode.12660.

Sanders, Taren, Philip D. Parker, Borja del Pozo-Cruz, Michael Noetel, and Chris Lonsdale. 2019. “Type of screen time moderates effects on outcomes in 4013 children: Evidence from the Longitudinal Study of Australian Children.” *International Journal of Behavioral Nutrition and Physical Activity* 16 (117). https://doi.org/10.1186/s12966-019-0881-7.

Santini, Ziggi Ivan, Paul E Jose, Erin York Cornwell, Ai Koyanagi, Line Nielsen, Carsten Hinrichsen, Charlotte Meilstrup, Katrine R Madsen, and Vibeke Koushede. 2020. “Social disconnectedness, perceived isolation, and symptoms of depression and anxiety among older Americans (NSHAP): a longitudinal mediation analysis.” *The Lancet Public Health* 5 (1): e62–e70.

Scholz, Urte, Benicio Gutiérrez-Doña, Shonali Sud, and Ralf Schwarzer. 2002. "Is general self-efficacy a universal construct? Psychometric findings from 25 countries." *European Journal of Psychological Assessment* 18 (3): 242–251.

Schoon, Ingrid. 2021. "Towards an Integrative Taxonomy of Social-Emotional Competences." *Frontier Psychology* 12 (515313). https://doi.org/10.3389/fpsyg.2021.515313.

Schoon, Ingrid, and Mark Lyons-Amos. 2016. "Diverse pathways in becoming an adult: The role of structure, agency and context." *Research in Social Stratification and Mobility* 46 (1): 11–20. https://doi.org/10.1016/j.rssm.2016.02.008.

Schoon, Ingrid, Bilal Nasim, and Rose Cook. 2021. "Social inequalities in early childhood competences, and the relative role of social and emotional versus cognitive skills in predicting adult outcomes." *British Educational Research Journal* 47 (5): 1259–1280. https://doi.org/https://doi.org/10.1002/berj.3724. eprint: https://bera-journals.onlinelibrary.wiley.com/doi/pdf/10.1002/berj.3724. https://bera-journals.onlinelibrary.wiley.com/doi/abs/10.1002/berj.3724.

Schultz, Theodore W. 1961. "Investment inhuman capital." *The American Economic Review* 51 (1): 1–17. ISSN: 00028282. http://www.jstor.org/stable/1818907.

Schurer, Stefanie. 2017. "Bouncing back from health shocks: Locus of control and labor supply." *Journal of Economic Behavior & Organization* 133:1–20. ISSN: 0167-2681. https://doi.org/10.1016/j.jebo.2016.10.019.

Schwarzer, Ralf, and Matthias Jerusalem. 1995. "Generalized self-efficacy scale." In *Measures in health psychology: A user's portfolio. Causal and control beliefs,* edited by Marie Johnston, John Weinman, and Stephen C Wright, 35–37. Windsor, UK: NFER-NELSON.

Seid, Yared, and Shiferaw Gurmu. 2015. "The role of birth order in child labour and schooling." *Applied Economics* 47 (49): 5262–5281. https://doi.org/10.1080/00036846.2015.1047086. eprint: https://doi.org/10.1080/00036846.2015.1047086. https://doi.org/10.1080/00036846.2015.1047086.

Sheehan, Peter, Kim Sweeny, Bruce Rasmussen, Annababette Wils, Howard S Friendman, Jacqueline Mahon, George C Patton, et al. 2017. "Building the foundations for sustainable development: A case for global investment in the capabilities of adolescents." *The Lancet* 390 (10104): P1792–1806. https://doi.org/10.1016/S0140-6736(17)30872-3.

Short, Michelle A., Stephen A. Booth, Omar Omar, Linda Ostlundh, and Teresa Arora. 2020. "The relationship between sleep duration and mood in adolescents: A systematic review and meta-analysis." *Sleep Medicine Reviews* 52:101311. ISSN: 1087-0792. https://doi.org/10.1016/j.smrv.2020.101311. https://www.sciencedirect.com/science/article/pii/S108707922030054X.

Singh, Abhijeet. 2019. "Learning More with Every Year: School Year Productivity and International Learning Divergence." *Journal of the European Economic Association* 18, no. 4 (June): 1770–1813. ISSN: 1542-4766. https://doi.org/10.1093/jeea/jvz033. eprint: https://academic.oup.com/jeea/article-pdf/18/4/1770/33680044/jvz033.pdf. https://doi.org/10.1093/jeea/jvz033.

Solaz, Anne, and François-Charles Wolff. 2015. "Intergenerational Correlation of Domestic Work: Does Gender Matter?" *Annals of Economics and Statistics,* nos. 117/118, 159–184. http://www.jstor.org/stable/10.15609/annaeconstat2009.117-118.159.

Soto, Christopher J., Christopher M. Napolitano, and Brent W. Roberts. 2021. "Taking Skills Seriously: Toward an Integrative Model and Agenda for Social, Emotional, and Behavioral Skills." *Current Directions in Psychological Science* 30 (1): 26–33. https://doi.org/10.1177/0963721420978613.

Southerton, Dale. 2003. "'Squeezing Time': Allocating Practices, Coordinating Networks and Scheduling Society." *Time & Society* 12 (1): 5–25. ISSN: 0961-463X. https://doi.org/10.1177/0961463X03012001001.

Spinney, Jamie, and Hugh Millward. 2010. "Time and Money: A New Look at Poverty and the Barriers to Physical Activity in Canada." *Social Indicators Research* 99 (2): 341–356. https://doi.org/10.1007/s11205-010-9585-8.

Staikov, Zahari. 1982. *It's about Time.* Institute of Sociology at the Bulgarian Academy of Sciences, Bulgarian Sociological Association. https://books.google.co.uk/books?id=4JAbAQAAMAAJ.

Stalsberg, Ragna, and Andre Pedersen. 2010. "Effects of socioeconomic status on the physical activity in adolescents: A systematic review of the evidence." *Scandinavian Journal of Medicine & Science In Sports* 20:368–383.

Stiglic, Neza, and Russell M. Viner. 2019. "Effects of screentime on the health and well-being of children and adolescents: a systematic review of reviews." *BMJ Open* 9 (1): 1–15. https://doi.org/10.1136/bmjopen-2018-023191.

Stillman, Steven, and Malathi Velamuri. 2020. *Are personality traits really fixed and does it matter?* IZA Discussion Paper 13342. Bonn, Germany: Institute of Labor Economics. https://doi.org/dx.10.2139/ssrn.3627043.

Stoet, Gijsbert, and David C. Geary. 2018. "The Gender-Equality Paradox in Science, Technology, Engineering, and Mathematics Education." *Psychological Science* 29 (4): 581–593. https://doi.org/10.1177/0956797617741719.

Sussman, Rachel F, and Robert Sekuler. 2022. "Feeling rushed? Perceived time pressure impacts executive function and stress." *Acta psychologica* 229:103702. https://doi.org/10.1016/j.actpsy.2022.103702.

Tafere, Yisak, and Alula Pankhurst. 2015. "Children combining school and work in Ethiopian communities." In *Children's Work and Labour in East Africa: Social Context and Implications for Policy,* edited by Alula Pankhurst, Michael Bourdillon, and Gina Crivello, 111–132. PO Box 31971, Addis Ababa, Ethiopia: Organisation for Social Science Research in Eastern / Southern Africa (OSSREA). http://www.ossrea.net.

Terraciano, Antonio, Robert R McCrae, and Paul T. Costa Jr. 2010. "Intra-individual change in personality stability and age." *Journal of Research in Personality* 44 (1): 31–37. https://doi.org/10.1016/j.jrp.2009.09.006.

Todd, Petra, and Kenneth I. Wolpin. 2007. "The production of cognitive achievement in children: Home, school, and racial test score gaps." *Journal of Human Capital* 1 (1): 91–136. https://doi.org/https://doi.org/10.1086/526401.

Trost, Stewart G., Neville Owen, Adrian E. Bauman, James F. Sallis, and Wendy Brown. 2002. "Correlates of adults' participation in physical activity: review and update." *Medicine & science in sports & exercise* 34 (12): 1996–200. https://doi.org/10.1097/00005768-200212000-00020.

Twenge, Jean M., Brian H. Spitzberg, and W. Keith Campbell. 2019. "Less in-person social interaction with peers among U.S. adolescents in the 21st century and links to loneliness." *Journal of Social and Personal Relationships* 36 (6): 1892–1913. https://doi.org/10.1177/0265407519836170.

UNICEF. 2021a. *The Changing Childhood Project.* Report. Gallup World Poll survey items used in the poll are Copyright ©2021 Gallup, Inc. Retrieved from UNICEF webpage. New York. https://www.unicef.org/globalinsight/reports/changing-childhood-project.

———. 2021b. *The state of the world's children 2021: On my mind – promoting, protecting and caring for children's mental health.* Report. Retrieved from UNICEF webpage. New York. https://www.unicef.org/reports/state-worlds-children-2021.

University College London. 2021. *Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 15th Edition. UK Data Service. SN: 5545.* UCL Institute of Education, Centre for Longitudinal Studies. https://doi.org/10.5255/UKDA-SN-5545-7.

Vandenbosch, Laura, Jasmine Fardouly, and Marika Tiggemann. 2022. "Social media and body image: Recent trends and future directions." *Current Opinion in Psychology* 45:101289. ISSN: 2352-250X. https://doi.org/https://doi.org/10.1016/j.copsyc.2021.12.002. https://www.sciencedirect.com/science/article/pii/S2352250X21002414.

VanderWeele, Tyler J., Eileen McNeely, and Howard K. Koh. 2019. "Reimagining health—flourishing." *JAMA* 321:1667–1668. https://doi.org/10.1001/jama.2019.3035.

Veeravalli, Sunil Kumar. 2019. *A guide to the parsed/raw Time Use Diary data (TUD).* Technical Report. London, UK: Centre for Longitudinal Studies. http://doi.org/10.5255/UKDA-SN-8156-7.

Veselska, Zuzana, Andrea Madarasova Geckova, Beata Gajdosova, Olga Orosova, Jitse P. van Dijk, and Sijmen A. Reijneveld. 2009. "Socio-economic differences in self-esteem of adolescents influenced by personality, mental health and social support." *European Journal of Public Health* 20 (6): 647–652. https://doi.org/10.1093/eurpub/ckp210.

Vincente-Benito, Irene, and María del Valle Ramírez-Durán. 2023. "Influence of Social Media Use on Body Image and Well-Being Among Adolescents and Young Adults: A Systematic Review." *Journal of Psychosocial Nursing and Mental Health Services* 61 (12): 11–18. https://doi.org/10.3928/02793695-20230524-02. eprint: https://journals.healio.com/doi/pdf/10.3928/02793695-20230524-02. https://journals.healio.com/doi/abs/10.3928/02793695-20230524-02.

Wanless, Shannon B., Megan M. McClelland, Xuezhao Lan, Seung-Hee Son, Claire E. Cameron, Frederick J. Morrison, Fu-Mei Chen, et al. 2013. "Gender differences in behavioral regulation in four societies: The United States, Taiwan, South Korea, and China." *Early Childhood Research Quarterly* 28 (3): 621–633. ISSN: 0885-2006. https://doi.org/doi.org/10.1016/j.ecresq.2013.04.002.

Watts, Geoffrey. 2020. "COVID-19 and the digital divide in the UK." *The Lancet, Digital Health* 2 (8): E395–E396. https://doi.org/10.1016/S2589-7500(20)30169-2.

Webster, Deborah, Laura Dunne, and Ruth Hunter. 2021. "Association Between Social Networks and Subjective Well-Being in Adolescents: A Systematic Review." *Youth & Society* 53 (2): 175–210. https://doi.org/10.1177/0044118X20919589.

Weiss, Felix, Markus Klein, and Thomas Grauenhorst. 2014. "The effects of work experience during higher education on labour market entry: learning by doing or an entry ticket?" *Work, employment and society* 28 (5): 788–807. https://doi.org/10.1177/0950017013506772.

West, Candace, and Don H. Zimmerman. 1987. “Doing gender.” *Gender and Society* 1:125–151.

WHO. 2014. *Health for the world’s adolescents: A second chance in the second decade: summary.* Technical document. Retrieved from the WHO website. Geneva: World Health Organization. https://www.who.int/publications/i/item/9789241512343.

———. 2017. *Global Accelerated Action for the Health of Adolescents (AA-HA!): Guidance to support country implementation.* Technical document. Retrieved from the WHO website. Geneva: World Health Organization. https://www.who.int/publications-detail-redirect/9789241512343.

———. 2020. *Guidelines on mental health promotive and preventive interventions for adolescents.* Report. Retrieved from the WHO website. Geneva: World Health Organization. https://www.who.int/publications/i/item/9789240011854.

Wigfield, Allan, and Jacquelynne S. Eccles. 2000. “Expectancy–Value Theory of Achievement Motivation.” *Contemporary Educational Psychology* 25 (1): 68–81. ISSN: 0361-476X. https://doi.org/10.1006/ceps.1999.1015.

Williams, John E, and Deborah L Best. 1990. *Sex and psyche: Gender and self viewed cross-culturally.* Sage. https://doi.org/10.1037/pspp0000078.

Winstone, Lizzy, Becky Mars, Claire M A Haworth, Jon Heron, and Judi Kidger. 2022. “Adolescent social media user types and their mental health and well-being: Results from a longitudinal survey of 13-14-year-olds in the United Kingdom.” *JCPP Advances* 2 (2): e12071. https://doi.org/https://doi.org/10.1002/jcv2.12071.

Wood, Wwndy, and Alice H Eagly. 2000. “A cross-cultural analysis of the behavior of women and men: implications for the origins of sex differences.” *Psychological Bulletin* 128:699–727. https://doi.org/10.1037/0033-2909.128.5.699.

World Bank. 2018. Data retrieved from World Development Indicators. https://data.worldbank.org.

Yamada, Shoko, and Christian S. Otchia. 2022. “Differential effects of schooling and cognitive and non-cognitive skills on labour market outcomes: The case of the garment industry in Ethiopia.” *International Journal of Training and Development* 26 (1): 145–162. https://doi.org/https://doi.org/10.1111/ijtd.12252.

Yogman, Michael, Andrew Garner, Jeffrey Hutchinson, Kathy Hirsh-Pasek, and Roberta Michnick Golinkoff. 2018. “The power of play: A pediatric role in enhancing development in young children.” Edited by Rebecca Baum, Thresia Gambon, Arthur Lavin, Gerri Mattson, Lawrence Wissow, David L. Hill, Nusheen Ameenuddin, et al. *Pediatrics* 142 (3). ISSN: 0031-4005. https://doi.org/10.1542/peds.2018-2058.

Yorke, Louise, and Maria José Ogando Portela. 2018. *Psychosocial scales in the Young Lives Round 4 survey selection, adaptation and validation.* Technical Note 45. Oxford, United Kingdom: Young Lives, University of Oxford. https://www.younglives.org.uk/publications.

Youngstrom, Eric A, Robert L Findling, and Joseph R Calabrese. 2003. “Who are the comorbid adolescents? Agreement between psychiatric diagnosis, youth, parent, and teacher report.” *Journal of Abnormal Child Psychology* 31:231–245. https://doi.org/10.1080/02671522.2019.1697734.

Zŭkauskiene, Rita. 2014. “Adolescence and well-being.” In *Handbook of child well-being. Theories, methods and policies in Global Perspective,* edited by Asher Ben-Arieh, Ferran Casas, Ivar Frønes, and Jill E.Korbin, 2:1713–1738. Netherlands: Springer Dordrecht.