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Essays on Regional Labour Markets

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Declaration

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.

I declare that my thesis consists of approximately 38,000 words, excluding the abstract and bibliography.

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This thesis spends quite some time talking about skills and education. If there is one thing I discovered while writing it, it is that doing a PhD is above all else an apprenticeship. There is only so much that can be learned from reading books (although there was also a fair amount of that). I was fortunate enough to learn from some of the best.

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Abstract

The thesis empirically studies drivers and determinants of incomes at the regional level in the United Kingdom. It draws on literatures in labour and macro economics, and examines these through a regional lens. The thesis contains three self-contained chapters.

Chapter 2 studies the effect of labour mobility on local earnings in Great Britain in the context of large regional earnings differences. Using a panel of employee records, I estimate the effect of internal in- and out-migration on the earnings of employees who do not move. Over the course of three years, the effect of in-migration on earnings growth is positive, with no adverse effect from out-migration. These effects are larger in urban areas, consistent with agglomeration effects as the underlying mechanism.

Chapter 3 considers the effect of growing industry concentration within the UK on regional earnings. Using detailed firm-level data, I show that the share of output produced by dominant firms has increased since 2002. While firms with market power pay higher wages, the labour share, the share of total value added earned by workers is lower. This is consistent with a rent-sharing model, whereby dominant firms charge mark-ups that are only partially shared with workers.

In chapter 4, I study technological invention as a driver of employment growth for different skill groups in NUTS1 and NUTS2 regions in Germany, France and the UK. Invention, proxied by patenting, has a positive effect on graduate employment. Both graduate employment and patenting have positive effects on mid-skilled and non-graduate employment, but these effects tend to be temporary, with no persistent increase in employment. Looking at the three countries individually, the results are suggestive of significant differences that can be rationalised with reference to differences in labour market institutions and innovation systems.

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Chapter 1

Introduction

This thesis is comprised of three empirical essays that investigate drivers of average regional earnings and income inequality between regions. Essays one and two focus on the United Kingdom, while essay three adds France and Germany in comparison to the UK. It draws on and contributes to literatures primarily in regional science and labour economics. The common theme across the essays is to understand drivers of earnings at the regional level, and to understand why earnings in some regions, within the same country, are so much higher than in others. To this end, I apply theories and methods from labour and macro economics to the regional level, focussing on three different drivers of earnings growth. The UK is chosen as the focus of the analysis, as a country with high and persistent inequality between regions. The UK also represents a specific variety of capitalism, as a European country that is more closely aligned with US liberalism.

While the focus of the thesis is on inequality in terms of wage incomes, inequality runs deeper than the purely economic level. The 2016 vote to leave the European Union is largely interpreted as a revolt by areas that have been excluded from the benefits of globalisation and technological progress. Aside from the political impacts, income inequality has further effects that are deeply unfair, if not damaging to the prospects of the country as a whole. These include disparities in educational attainment, social mobility, general health, and life expectancy.

For this thesis, I study causes of regional income differences from different angles. The first essay studies the effect of internal migration on local earnings. The second essay considers market power and dominant firms as drivers of regional earnings and labour shares. The third essay explores the effect of technological invention on employment for different skill groups. In this chapter, section 1.1 elaborates on the motivation for the thesis. Section 1.2 provides an overview of the three essays, concluding with a summary of the overall contribution of the thesis in section 1.3.

1.1.Motivation

Regional inequality is a long-standing issue in the UK economy (Massey, 1979). While London is among the richest regions in Europe, some regions in Wales and the North East are among the poorest. The success of London as a driver of national growth has long overshadowed the stagnation and decline of regions that did not benefit from globalisation and the transformation of the service economy. Despite its specialisation in the financial sector, London was relatively unscathed by the financial crisis (Overman, 2011). Moreover, already struggling regions were hit hardest by the austerity polices that followed (Fetzer, 2019).

While one chapter of the thesis explores the effects of internal migration on regional inequalities, most people in the UK in fact never move very far away from where they were born (Bosquet & Overman, 2019). Place of birth also determines other life outcomes (Chetty, Hendren, Kline, & Saez, 2014; Chetty, Hendren, Lin, & Majerovitz, 2016), and many people have strong preferences to stay in a place they grew up in and where they benefit from strong networks. It is therefore important to create opportunities across the country, not just in a few, highly successful places.

Unfortunately, the negative effects or considerable adjustment costs of economic change on some regions or individuals have often been dismissed or underestimated. For example, while foreign direct investment and trade have overall positive effects on national economies, certain regions may be particularly exposed due to their skill and industry mix (Autor, Dorn, & Hanson, 2013; Gagliardi, Iammarino, & Rodríguez-Pose, 2021). The adjustments to these structural changes come at a high economic (Autor, Dorn, Hanson, & Song, 2014), personal (Goldstein, 2017) and political cost (Becker, Fetzer, & Novy, 2017; Rodríguez-Pose, 2018).

The goal of this thesis is to apply theories and concepts from labour and macro economics to the regional scale, to understand how they not only affect outcomes, but also inequalities between regions. The UK provides a good context for this. Firstly, because inequalities are deep and persistent. Secondly, because the political system is highly centralised, with little variation in formal institutions and policies across regions and cities

(Pike, Rodríguez-Pose, Tomaney, Torrisi, & Tselios, 2012). While some areas of policy making are the responsibility of the devolved administrations of Scotland, Wales and Northern Ireland, most policy decisions are made centrally by the national government in Westminster. Local governments and the increasing number of mayors can shape local priorities, but have little ability to raise taxes and therefore to direct local spending. The uniformity of institutions across the country allows to focus on the underlying economic mechanisms with high external validity in other contexts. While there are many structural economic differences across regions, the focus of the thesis is on more recent trends that are defining recent regional growth trajectories.

Economics has long been grappling with explaining differences in economic development across territories. Indeed, for a long time, it was assumed that incomes would converge, conditional on differences in technology and human and physical capital (Mankiw, Romer, & Weil, 1992; Romer, 1994). The New Economic Geography developed formal models to demonstrate why differences in income may persist (Fujita, Krugman, & Venables, 1999). From recognising that not all regions are equal, a lot of attention has been paid to the particular advantages of cities (Duranton & Puga, 2004; Glaeser, 2011; Storper, 2013). This thesis adds to this literature by studying several mechanisms that drive wages at the regional level.

1.2. Overview of the thesis

The thesis draws together three independent essays, each studying regional income inequalities from a different angle. Chapter 2 considers the effect of internal migration, chapter 3 studies the effect of market power and industry concentration, and chapter 4 explores the impacts of technological invention. The following provides a brief overview of each chapter. The main message of the thesis is that local labour markets are highly complex and shaped by a variety of forces. The thesis provides insights into some of these forces that have so far received relatively less attention.

1.2.1 First essay

Chapter 2 estimates the effect of internal migration in Great Britain on earnings of those who do not move. The effect of graduate migration has been studied extensively in the UK context (Faggian & McCann, 2009; Faggian, Rajbhandari, & Dotzel, 2017). Likewise, there is abundant evidence of the (limited) effect of immigration on local labour markets (e.g. Dustmann, Frattini, & Preston, 2013). However, mobility of employees during their working lives has received relatively little attention. Descriptive analysis confirms wide differences in average earnings between local labour markets, even after controlling for individual observable characteristics. These inequalities beg the question: why do individuals not simply move to an area where they can expect to earn more? And as people move, why do these inequalities not decline over time? While differences in nominal earnings may compensate for differences in the cost of living or the availability of local amenities (Glaeser & Gottlieb, 2009), there is evidence for real inequalities in welfare across regions, even after controlling for these factors (Kemeny & Storper, 2012). While skills mismatches may be a motivation to migrate (Iammarino & Marinelli, 2015), a lack in skills may also prevent those from a region where wages are low to move to a region where wages are higher (Giannone, 2018).

The chapter develops a simple model of earnings, which depend on labour supply as well as productivity, whereby productivity is endogenously determined by the local labour force. Therefore, internal migration can affect both labour supply, where it is expected that an increase in labour supply will have a negative effect on wages, as well as productivity, where it is expected that in-migration will increase productivity and wages.

The chapter draws on the Annual Survey of Hours and Earnings, a 1% sample of all employees in the UK, to develop a measure of labour migration between travel-to-work areas (TTWAs), representing self-contained local labour markets. Descriptive analysis confirms that internal migrants experience an increase in earnings upon migration. However, this is mostly driven by the effect of starting a new job. After controlling for this, many internal migrants seem to be motivated by factors other than earnings, implying that internal in- and out-migration may be credibly described as exogenous shocks to local labour supply. The results show an immediate negative effect of in-migration on the earnings of those who do not move, consistent with the labour supply effect. However, this turns positive over three years, consistent with the productivity effect. These effects are larger in urban areas, suggesting that the density and buzz of cities may be conducive to the productivity enhancing effect of internal migrants. Conversely, there is no effect of out-migration, either in the short or medium term.

1.2.2 Second essay

Chapter 3 studies the effect of industry concentration and market power on regional labour markets. Increasing market power of dominant firms is of growing concern globally, both from a consumer and worker perspective (Eeckhout, 2021; Philippon, 2019). In particular, this has been linked to a decline in the labour share, the share of total value added earned by workers (Autor, Dorn, Katz, Patterson, & Van Reenen, 2020; Barkai, 2020). While falling labour shares have been documented globally (Dao, Das, Koczan, & Lian, 2017; Karabarbounis & Neiman, 2013), the issue has not been studied from a regional perspective.

The chapter shows that industries that become more dominated by a small number of large firms are also more regionally concentrated. This suggests an important role of these businesses for local economies. Dominant firms are under increasing scrutiny, because their market power allows them to charge a mark-up over marginal cost, creating a wedge between labour productivity and wages. If sales and labour productivity increase due to growing mark-ups, wages remain stagnant and the labour share falls if labour markets are perfectly competitive. This would imply a growing concentration of wealth in the hands of business owners, and less in the hands of workers. Yet, models of efficiency wages explain why it may be in a firm's interest to share some of the mark-up with workers. Rent sharing would result in higher wages at the firm level, with ambiguous effects on the labour share.

I test these hypotheses on a sample of UK businesses drawn from the Annual Respondents Database X (ARDX). Descriptive analysis documents three important stylised facts. First, industry concentration in the UK has increased considerably between 2002 and 2014 on a wide range of indicators. Second, industries where market power is high are also highly regionally clustered. And third, most dominant firms can be found in London and the wider South East region. Regression analysis shows that firms with market power pay higher wages, suggesting that rent sharing is taking place. However, these firms also have lower labour shares, suggesting that only a fraction of rents is shared with workers. Yet, the impacts at the regional level are limited. In London and the South East, the strong presence of dominant firms is counteracted by a large number of very small businesses. This suggests that more research on the impact of dominant firms on inequality within regions is warranted.

1.2.3 Third essay

Chapter 4 considers the employment effects of technological invention, measured by patent filings, in France, Germany and the UK. The interdependence between innovation and local human capital is well documented. Recent research has highlighted the importance of multiplier effects, whereby high-paid workers – such as those working in innovative industries – create more local jobs through local consumption, mainly for those without a university degree (Lee & Clarke, 2019; Kemeny & Osman, 2018; Moretti, 2012). This also feeds into theories of labour market polarisation, whereby employment growth is strongest at the high- and low-paid ends of the labour market, with jobs in the middle becoming more and more scarce (Autor & Dorn, 2013; Goos, Manning, & Salomons, 2014). The question this chapter seeks to answer is two-fold. First, can the generation of new technology create jobs for those without a university degree? Second, are there any multiplier effects from technological invention or graduate employment for those with intermediate skills, defined as having an advanced vocational qualification?

I approach these questions using aggregate regional data at the NUTS1 and NUTS2 level. In contrast to previous studies, I take into account that the multiplier effects are likely to be dynamic, with effects taking time to materialise and disappearing again after some time. To allow for this, I estimate the effects using local projections (Jordà, 2005). I confirm previous findings of positive effects of patenting on graduate employment, and of graduate employment on non-graduate employment. Additionally, I also find evidence of positive, albeit short-lived effects of patenting on non-graduate and mid-skilled employment.

Given the differences in educational and innovation systems across the three countries studied, considerable heterogeneity in the effects can be expected among them. Germany is most active in patenting among the three, and innovative activity is the most spread out across subnational regions. Both France and Germany have a tradition of vocational education that is absent in the UK. Unfortunately, owing to limited data availability, the investigation into cross-country heterogeneity remains suggestive at this stage.

1.3.Contribution and limitations

Regional income differences are driven by a variety of factors, including, but not limited to, industry and labour force composition, demographics, and formal and informal institutions (Storper, Kemeny, Makarem, & Osman, 2015). Each chapter of the dissertation contributes to a different strand of research, including migration studies, industrial organisation, and technological innovation studies. Each chapter identifies gaps in the relevant literatures that are addressed with reference to the case studied. However, there are some common themes that advance the overall contribution of the thesis.

Regional inequality in the UK is often portrayed to be geographically uni-dimensional: between the North and the South, between old manufacturing and technologically advanced regions, between the winners and losers of globalisation. The analysis presented in this thesis shows that the drivers of regional inequality are manifold. The results support a relatively new cleavage in the British context, between large urban areas and smaller towns and rural areas. The large cities of the Midlands and the North have lagged behind the success of London. However, they now seem to benefit from some of the same forces as London. For example, chapter 2 shows that larger cities benefit more from internal migration than non-urban areas.

Chapters 2 and 3 rely on individual- and firm-level data to answer regional-level questions. While trends in regional averages are important, the micro-level allows taking into account heterogeneity within regions. Microeconomic research provides insights into the drivers and outcomes of individual behaviour, as well as the effects of outside forces on individual outcomes. The goal here is to explain the opposite effect, to provide evidence of the microfoundations for aggregate, regional outcomes. This poses challenges for causal inferences, as the actions of firms and individuals both contribute to aggregate outcomes, but are also affected by the regional environment. The chapters in this thesis try to solve these problems by developing theoretical frameworks grounded in the literature that can guide the analysis. This is combined with careful descriptive analysis to provide evidence for the underlying mechanisms.

The thesis has some limitations. It focuses on the relatively recent past, and the effects of short-term changes. Many of the territorial inequalities in the United Kingdom have their roots in the long-term structural decline of some industries. Some of the regions that are now relatively deprived were once among the richest in the world and at the heart of the industrial revolution which started in Britain (Allen, 2009). Other regions and industries were shaped by the British Empire and colonial trade (Jones, 2002; Sunderland, 2013). While the legacies of industrial revolution and empire still influence the modern UK in many ways, the focus here is on current economic change and factors that can be controlled, at least to some extent, by policy makers today. Unfortunately, Northern Ireland, with an economic and political history of its own, could not be included in the analyses in chapters 2 and 3 due to data limitations.

While the focus of the thesis is on inequality between regions, there are other dimensions of inequality (Bourguignon, 2015, ch. 1). While London is referred to throughout this thesis as the region in the UK with the highest average income, the city is also home to some of the most deprived neighbourhoods of the country. Furthermore, there are aspects of inequality without an explicit spatial scale, between workers in different occupations, with different levels of education, between ethnic groups, men and women, and generations. While important issues in themselves, the thesis only makes limited contributions to these problems. Furthermore, the empirical analysis only considers labour income, mostly of employees, in the formal sector. This leaves out the incomes and welfare of those out of the labour force, as well as the self-employed and those working in the informal economy.

In conclusion, the main contribution of this thesis is to identify recent drivers of income growth at the regional level, and explains how these contribute to inequality between regions in the UK. It takes recent contributions in labour and macro economics and applies these to the regional scale. It provides insights into how these forces play out across different regions, contributing to ongoing debates on the sources of and policy response to persistent inequality between UK regions. It also provides a wide range of descriptive insights that I hope will encourage and shape further research into these topics.

Chapter 2

Labour mobility and regional earnings in Great Britain

2.1.Introduction

Regional income inequality in the UK is high and persistent, reflecting both differences in skill endowments as well as differences in returns to skills (Duranton & Monastiriotis, 2002). While some of these differences are compensated by differences in the cost of living, disparities are mirrored in unemployment, GDP per capita (Martin, Pike, Tyler, & Gardiner, 2016), child poverty (Hood & Waters, 2017), and social mobility (Social Mobility Commission, 2017). Faced with stark inequality, movements from low-income to high-income regions could both give individuals an instant boost to earnings as well as eradicate regional earnings differences over time. However, despite relatively high levels of labour mobility (Tatsiramos, 2009), earnings inequality in the UK remains high.

In this chapter, I study the impact of internal migration[1] on regional earnings in the UK. I find rates of labour mobility of around 7% among employees each year. These moves are highly diverse: there is no single pattern of internal migrations. While many people move to London and the wider South East, coastal areas also saw surprisingly high inflows of employees. On average, internal migrants experience a boost to their earnings upon migration, but this varies considerably by destination, occupation and age. Inflows

[1]In the following *migrants* refers exclusively to those moving within the UK. I refer to those moving to the UK from abroad or vice versa as *immigrants* or *emigrants*.

of internal migrants to a local labour market exert downward pressure on wages at first, consistent with a classic labour supply and demand framework. However, over the course of three years, this turns into a positive effect on wage growth, which is stronger in urban areas. In contrast, out-migration from a local labour market does not have a significant effect on the earnings of those staying behind, neither in the short or longer term. Overall, the findings imply positive effects of labour mobility, both on internal migrants and non-migrants.

Regional inequality in the UK remains a pressing problem and the subject of many policy debates – in particular in the aftermath of the 2016 vote to leave the European Union and the regional divides it has revealed. It is widely understood that internal migration has positive earnings effects, at least for full-time employees. Yet, there is little evidence on how internal migrant flows affect local labour markets. The chapter is most closely related to Mitze and Schmidt (2015), who study the effects of internal migration on regional incomes in Denmark. Faggian and McCann (2009) and Iammarino and Marinelli (2015) estimate the effects of graduate migration on regional economies in the UK and Italy, respectively. Combes, Duranton, and Gobillon (2008), D'Costa and Overman (2014) and Duranton and Monastiriotis (2002) rely on internal migrants to identify city wage premia. In contrast, the goal of this chapter is to estimate the effects of internal migrants, and specifically employees moving mid-career, on those who do not move.

The chapter proceeds as follows: Section 2.2 provides a review of the literature, which forms the basis for the theoretical framework. The dataset and empirical strategy are presented in section 2.3. Section 2.4 presents the results, first extensively characterising internal migration flows in the UK and then estimating their effect on local earnings. Section 2.5 concludes.

2.2.Related literature and theoretical framework

There is an extensive literature on the effect of immigration from abroad on local earnings. Internal migration has been studied relatively less, with a focus on the effects of migration on the migrants themselves, rather than the wider impacts of labour mobility. The following provides a brief overview of the evolution of regional inequalities in the UK, and with respect to wages in particular. I provide a short introduction into the literature on wage determination and explanations behind the persistence of regional differences, followed by the role internal migration might play in these. This is summarised in the theoretical framework as the basis for the following analysis.

2.2.1 Local earnings and regional inequality

The large gaps between rich and poor regions in the UK are widely cited to be one of the reasons behind the 2016 vote to leave the European Union (Becker et al., 2017), and are an important matter for government policy (HM Government, 2017). Not only in the UK, but in many developed countries has a combination of technological change and globalisation forces led to growing regional economic polarisation that is yet difficult to explain in its extent and wider implications (Storper, 2018). The UK is the OECD country with the sharpest decline in manufacturing employment since 1970, which exacerbated existing income inequalities between northern and southern regions. This is not a new phenomenon, but rather a reversal of the decline in inequality that the country experienced during the post-war period. This in turn resulted out of changing national and international divisions of labour in conjunction with the regional concentration of declining industries in the UK (Massey, 1979). Measured in GDP per capita, regional inequality is among the highest in the UK compared to other west European countries and has been rising steadily since the 1970s (Martin et al., 2016). Economic decline in the North was met with population decline, which only stopped in the 2000s when immigration from abroad into those regions picked up (Coutts, Glyn, & Rowthorn, 2007).

Regional inequality is on the rise in many countries, not just the UK. In recent years, the most successful areas have been large urban agglomerations. However, it is not only the agglomeration of well-educated people that makes these places successful. Cities themselves also add to the productivity of their workers. Wages are generally higher in cities than in rural areas, but workers moving to urban areas also experience faster wage growth than their peers in rural areas. These gains stick with workers even once they leave an urban area, indicating that cities increase the skills of their workforces (Glaeser & Maré, 2001; Champion, 2013; D'Costa & Overman, 2014; De la Roca & Puga, 2017). Duranton and Monastiriotis (2002) show that regional income gaps in the UK are increasingly explained by segregation by skill, whereby high-skilled workers sort into high-earning areas, and those with less education into low-earning areas. In contrast, the returns to skill have converged across regions.

Contributing to the divergence between regions is the widening gap between earnings of high- and low-skilled individuals. This wage polarisation occurs along two lines. The number of relatively well paid jobs in manufacturing and medium-skilled service occupations is shrinking due to import competition (Autor et al., 2013) and skill-biased technological change (Machin, 2001). The workers benefiting from this trend can be found both at the top and the bottom of the pay distribution, as both complex cognitive tasks and many manual tasks and personal services are difficult to automate, outsource or offshore (Goos et al., 2014; Gagliardi, Iammarino, & Rodríguez-Pose, 2015).

In a basic framework, regional differences in wages are caused by mismatches of labour supply and demand. If this is the case, well integrated labour markets, where workers are able to swiftly react to wage differences across regions, may reduce regional inequality (Bachmura, 1959; Bonin et al., 2008; Lehmer & Ludsteck, 2010). However, not all demographic groups are equally able to adjust, and lower mobility has contributed to the relatively greater deterioration in employment and earnings of the lower skilled (Bound & Holzer, 2000). Mobility can also be lower during recessions, slowing down the adjustment to negative shocks (Jackman & Savouri, 1992; Saks & Wozniak, 2011). Following the financial crisis of 2008, cross-border mobility in the EU declined and remains on a low level, despite disparities in regional unemployment rates and labour shortages (Eurofound, 2014). Within countries of the European Union, inter-regional mobility is actually higher in countries with higher GDP per capita, although it is difficult to compare statistics across countries (Eurofound, 2014). University graduates are among the most mobile demographic groups (Faggian & McCann, 2009). Additionally, geographic mobility is an important factor in raising employment rates among graduates and improving skill-job match (Iammarino & Marinelli, 2015).

Over the longer term, regional earnings differences are more likely to be driven by differences in productivity. There are large differences in productivity between the regions of the UK. Some of this is explained by differences in industry specialisation, as some industries tend to be more productive than others (Gardiner, Martin, Sunley, & Tyler, 2013). Regional specialisations are highly path dependent and evolved over decades, if not centuries. Some parts of the North and the Midlands of England became very prosperous during the first Industrial Revolution, but have had a long period of decline from the 1970s with the onset of deindustrialisation. The manufacturing jobs that were lost during this period were largely replaced by low-skilled service sector jobs (Rowthorn, 2010). However, even within industries, there are regional differences. Even the most productive industries, such as high-skilled services, tend to have above average productivity in London and the South East and below average productivity in other regions (Gal & Egeland, 2018). There are many drivers of productivity at various levels, nationally, regionally, at the industry and individual firm level. Even within narrowly defined industries, there is a lot of between-firm heterogeneity in productivity that is reflected in between-firm heterogeneity in earnings (Barth, Bryson, Davis, & Freeman, 2016; Card, Cardoso, Heining, & Kline, 2018; Card, Heining, & Kline, 2013; Goux & Maurin, 1999; Van Reenen, 1996). Therefore, the place of work – both the location and the firm – are important determinants of wages.

Of course, individual characteristics, including observable and unobservable skills, also play an important role in determining earnings (Andersson et al., 2012; Abowd, Kramarz, & Margolis, 1994). In particular, there is increasing evidence of sorting of high-earning workers into high-paying firms, leading both to higher inequality between workers as well as firms (Card et al., 2013; Eeckhout & Kircher, 2011). The causality between employee skills, productivity and earnings runs in both directions. While workers benefit from higher firm level productivity, driven, among others, by capital intensity and technology, workers themselves are also important drivers of productivity (Barth, Davis, Freeman, & Wang, 2017; Galindo-Rueda & Haskel, 2005; Syverson, 2011). Hence, through localised productivity spillovers and agglomeration economies, internal migration may have effects on productivity and earnings (Groot, de Groot, & Smit, 2014; Mitze & Schmidt, 2015).

2.2.2 Drivers and effects of internal migration

Internal migration decisions – both whether to migrate, and the destination decision – are complex. Individuals maximise their utility on a range of different domains, balancing sometimes conflicting factors, such as income, career prospects, costs of living, amenities and individual preferences (Biagi, Faggian, & McCann, 2011; Greenwood, 1997; Kennan & Walker, 2011). The decision becomes even more difficult where it involves not only an individual person but a family, so that multiple incomes and preferences have to be taken into account (Mincer, 1978). There is a large body of literature concerning the motivations and outcomes of labour mobility and internal migration. Internal migrants tend to be younger, better educated, and experience a boost to their earnings upon migration (Greenwood, 1997). However, both the determinants of the decision to migrate, and the choice of destination are different for different skill groups, making it difficult to draw conclusions for overall flows (Piras, 2021).

A phenomenon that has been studied more recently, in particular in the context of high housing costs in the most productive cities worldwide, is labour sorting whereby the most productive individuals who can expect to earn high wages sort into the most productive cities. Costs of living are high in these cities, but the high-skilled can expect to maximise their earnings there. This influx of high-earners pushes out workers in less productive occupations and industries, who cannot afford to live in expensive cities. However, the presence of a large group of high-earners also creates a lot of low-skilled service jobs, resulting in rising inequality (Dahl, 2002; Diamond, 2016; Moretti, 2012).

When studying the mobility of individuals, most papers do find a positive effect of migration on migrants' wages (Bonin et al., 2008; Kennan & Walker, 2011). Identifying the causal effect of migration on wages is far from trivial as it requires controlling for unobserved selection bias. Furthermore, even for non-migrants who stay in the same job, wages are not static: workers' wages tend to increase as they accumulate experience, and location- and job-specific human capital. Therefore, a change of job and labour market also entails the loss of these assets. Nonetheless, empirical studies find both evidence of an instant pay premium upon migration, as well as higher pay growth over time (Böheim & Taylor, 2007; Rodríguez-Pose & Tselios, 2010; Yankow, 2003).

There are also many non-labour market related reasons to move. For example, people may decide to migrate for amenity reasons, such as good schools, a beautiful natural environment, an interesting cultural scene, to be closer to friends and family, or to follow their partner. Unsurprisingly, many authors studying family migration find no or even a negative effect of internal migration on household income (Clark & Davies Withers, 2006, 2007; Cooke, 2003; LeClere & McLaughlin, 1997). In some of the studies cited above only men are considered, and results might well be different if women were included (e.g., Böheim & Taylor, 2007; Yankow, 2003). For heterosexual couples, the negative effects on wives' wages are relatively short lived, but husbands' earnings are also largely unaffected by a move (Blackburn, 2010; Rabe, 2011; Lersch, 2012). Ultimately, the decision to migrate may be one of individual preferences. As will be shown below, those who migrated once are also more likely to migrate again. In the 2016 UK referendum on exiting the European Union, those living in their county of birth were 7% more likely to vote Leave if that area was also affected by relative economic decline (Lee, Morris, & Kemeny, 2018). This is just one example demonstrating that migration is an important life event, whether it signals or changes personal characteristics and opinions.

Internal migration might have larger effects on local earnings. However, it is unclear which direction these effects take: On the one hand, internal migration might serve to balance labour supply and demand, with out-migration leading to earnings growth and in-migration leading to a fall in wages. On the other hand, internal migrants might affect productivity through agglomeration economies and knowledge and skill spillovers. This chapter is closely related to Mitze and Schmidt (2015), who find evidence for a virtuous circle of agglomeration economies, which attract in-migrants, reinforcing agglomeration effects. The effects can be compared to those of immigration. While immigration is often found to have no overall effect on wages, there is evidence of small negative effects on the low-skilled (Dustmann et al., 2013; Manacorda, Manning, & Wadsworth, 2012). In contrast, low-skilled immigrants are often complementary to high-skilled workers, either in production or by providing cheaper or a larger variety of goods and services (Cortés, 2008; Cortés & Tessada, 2011). Patterns of internal migration and immigration are closely intertwined. Depending on the skill complementarities of immigrants and natives, immigration can attract (Mocetti & Porello, 2010; Peri, 2007) or displace natives (Borjas, 2006; Hatton & Tani, 2005). The internal migration response to immigration is therefore likely to be skill-dependent. Recent evidence for the UK shows that newly arriving immigrants do not have a displacement effect on natives, but on earlier waves of immigrants, especially the low-skilled (Giulietti, 2009). However, for developed economies, the effect of out-migration, sometimes characterised as a "brain drain" (Docquier & Rapoport, 2012) is rarely studied.

To summarise, internal migration can affect average local earnings through the skill composition and its effects on agglomeration economies. While earnings differentials are an important driver of migration flows, there are many other factors that influence migration decisions. The following translates this into a simple framework to guide the analysis.

2.2.3 Theoretical framework

In this section, I describe a simple theoretical framework to illustrate the effects of internal migration on local earnings, based on similar models developed by Combes et al. (2008), and Graham and Melo (2009). Suppose output Y in area a is produced according to a Cobb-Douglas production function using capital K_a and labour L_a:

$$Y_a = A_a(s_a L_a)^{\mu} K_a^{1-\mu} \tag{2.1}$$

Where A_a is total factor productivity (TFP) and s_a is the skill level of the labour force. If firms in the region are profit maximising, the returns to labour – the wage rate w_a – and capital – rents r – will be equal to their marginal product. We assume that capital is perfectly mobile, and therefore the cost of capital is the same across regions. However, wages are determined locally. For simplicity, the output price index is set to unity, yielding the profit function:

$$\Pi_a = A_a(s_a L_a)^{\mu} K_a^{1-\mu} - (w_a L_a + r K_a) \tag{2.2}$$

The first order conditions provide the returns to capital and labour:

$$r = (1-\mu) A_a s_a^{\mu} \left(\frac{K_a}{L_a}\right)^{-\mu} \tag{2.3}$$

and

$$w_a = \mu A_a s_a^{\mu} \left(\frac{K_a}{L_a}\right)^{1-\mu} \tag{2.4}$$

Equation 2.4 establishes the negative relation between labour supply and wage, all else equal. In the short-term, where labour demand does not adjust, internal in-migration increases labour supply L_a and wages are expected to fall. In contrast, out-migration from the area reduces labour supply and wages are expected to increase.

Equation 2.4 can be rearranged and plugged into equation 2.3, to yield the labour demand curve in equilibrium :

$$w_a = \mu(1-\mu)^{(1-\mu)/\mu} s_a \left(\frac{A_a}{r_a^{1-\mu}}\right)^{1/\mu} \tag{2.5}$$

Note that in equilibrium, wages no longer depend on the level of labour or capital. Instead, the equilibrium wage depends positively on the average skill level of the labour force s_a, positively on TFP A_a, and negatively on the cost of capital r. Internal migration may affect s_a, by affecting the skill mix in the area, for example if there is sorting and migrants tend to be higher skilled (Duranton & Monastiriotis, 2002). Note that s_a is the average skill level in the local area. For example, it is assumed that the share of workers with a degree will have an effect on the productivity and wages of all workers. Through this mechanism, internal migrants may affect average earnings in the areas they are joining or leaving (Barth et al., 2017; Faggian & McCann, 2009; Moretti, 2004). A related channel is through effects on TFP, A_a. Internal migrants may bring new knowledge and networks to an area, which raises TFP (Eriksson, 2011; Groot et al., 2014; McCann & Simonen, 2005; Power & Lundmark, 2004). In the empirical implementation of the model, we will not be able to distinguish the skills and TFP channels, however both serve to illustrate that internal migrants can affect average equilibrium wages.

The model is very simple and is only meant to illustrate two mechanisms through which internal migrants might affect local earnings. It assumes that internal migration is the only source of change in labour supply, abstracting from labour force participation, natural increase and decline, and immigration. There may be a negative feedback effect whereby previous residents are pushed out over time as house prices increase. The model also assumes perfect competition in labour markets. Firms may have wage setting power, and wages may be rigid due to other constraints such as long-term contracts and trade unions. If internal migrants contribute to productivity growth, firms do not necessarily share those gains with workers.

2.3.Data and empirical methods

Measuring migrant flows in the UK is difficult, as there is no population register. Official estimates rely on registrations with family doctors and movements of students in higher education (Office for National Statistics, 2016). Here, I identify migrants from a long-running employer survey that also provides information on internal migrants' earnings and place of work. This section describes how the dataset is constructed and how it will be used in the estimation.

2.3.1 Data

The Annual Survey of Hours and Earnings (ASHE) has been used frequently to address questions concerning local labour market conditions in the UK (e.g. Graham & Melo, 2009; Gibbons, Overman, & Pelkonen, 2014; D'Costa & Overman, 2014). As it identifies individuals through their working lives even as they change their place of work, it is uniquely suited to answer questions around internal migration and earnings. The individual-level datasets used in this study were accessed through the Office for National Statistics Secure Research Service.

ASHE is a 1% panel of pay-as-you-earn (PAYE) tax registered employees, who are identified by the last two digits of their national insurance number (NiNo). Questionnaires are completed by employers from information available on payslips, and the quality of the data is considered to be high. Because of the NiNo identifier, employees stay in the survey even if they change jobs. However, it is a known shortcoming that ASHE is less reliable for those on low incomes, as well as those who move jobs frequently, as there is a time lag between drawing the sample and sending out questionnaires. Only jobs that pay more than the personal tax allowance are reported to HM Revenues and Customs (HMRC), so jobs falling below this threshold are not picked up on ASHE. The personal allowance has gradually increased from £4,745 of annual earnings in 2004/05, where the main dataset for this study starts, to £11,850 in 2018/19. Also, self-employed workers are not included, therefore workers in the so-called *gig-economy*, but also independent contractors and self-employed professionals are not captured in the survey.

Since the dataset is a panel with an annual observation for each employee, it is possible to trace people as they move and change jobs. Each year, employees appearing on ASHE are identified as internal migrants if their travel-to-work area (TTWA) of employment is different to that of the previous year. Employees that were missing for one year only are also identified as migrants if the TTWA differs before and after the break. Employees with longer absences from the survey are not considered in identifying migrants. As only those in continuous employment are considered, graduates moving for their first job after finishing university cannot be included.

I use the postcode of the place of work to assign TTWAs, following D'Costa and Overman (2014). ASHE also provides the postcode of the home address, but this variable is less complete and potentially more noisy. TTWAs are designed so that 75% of workers in an area also live there, and 75% of residents in an area also work there. Hence, for most employees, the work and home TTWAs are the same (Office for National Statistics, 2015). Commuting patterns across TTWAs may be non-random, with high earners tending to commute further (Brown, Champion, Coombes, & Wymer, 2015). To avoid any biases that could stem from commuting patterns, I focus only on the place of work.

From an initial definition in 2001, TTWAs were updated in 2011 to reflect new census results (Coombes & Office for National Statistics, 2015). For consistency, the 2011 TTWAs are used throughout. The downside is that the further the analysis is moving away from 2011, the less reflective TTWAs are of actual commuting patterns at the time. Given that the density and capacity of road and public transport connections varies widely across the country, the size and shape of TTWAs is uneven. Within the 75% rule, boundaries were set to "maximise the number of self-contained areas" (Coombes & Office for National Statistics, 2015, p. 9), resulting in a number of relatively small TTWAs. To increase sample sizes in rural areas, some TTWAs were consolidated, bringing the total number down from 218 to 150 TTWAs of more even size (following Gibbons et al., 2014[2]). Furthermore, setting the boundaries of large cities is a difficult task. For example, in the east, the London TTWA contains much of the areas along the Thames Estuary, which are part of Essex and Kent. In the west, some London boroughs have been combined with Slough to form the Slough and Heathrow TTWA. However, TTWAs have not been modified further to facilitate comparability.

ASHE provides information on the hourly rate, usual hours worked, overtime and incentive pay, and the occupation and managerial duties of the employee, continuously for 1975 to 2018. Crucially, for 2004 to 2018, it also provides the postcode of employment. Throughout the chapter, earnings or wages refer to total gross weekly earnings, usually in logs, in an employee's main job. Some employees have more than one job. I retain only the main job, defined as the one with the highest hourly wage or most weekly hours worked, if hourly wages are the same. In the few cases where both earnings and hours are the same, the main job is chosen at random. As ASHE questionnaires are completed by employers, employer information such as industry and total employment are also included in the dataset. While data before 2004 cannot be linked to location, I use the historical data to compute total years of employment experience. As two time lags are required to identify the internal migrants, the analysis covers the years 2006 to 2018.

Occupations are coded to the main National Statistics Socio-Economic Classifications (NSSEC), which facilitates comparisons across time and classification regimes. There are seven main groups: higher managerial, lower managerial, administrative and professional; intermediate occupations; small employers and own account workers; lower supervisory and technical employees; semi-routine and routine occupations. As shown in table 2.1, these are summarised into three classes for the analysis – higher, middle and routine/ semi-routine occupations.

[2]Definitions and shapefiles for consolidated TTWAs based on 2001 boundaries were kindly provided by Steve Gibbons. These were updated by the author to reflect 2011 boundaries.

Table 2.1: Summary of NSSEC classes

	NSSEC class	Classes for analysis
1	Higher managerial, administrative and professional	Higher occupation
2	Lower managerial, administrative and professional	Higher occupation
3	Intermediate occupations	Middle occupation
4	Small employers and own account workers	Middle occupation
5	Lower supervisory and technical occupations	Middle occupation
6	Semi-routine occupations	Routine/ semi-routine
7	Routine occupations	Routine/ semi-routine

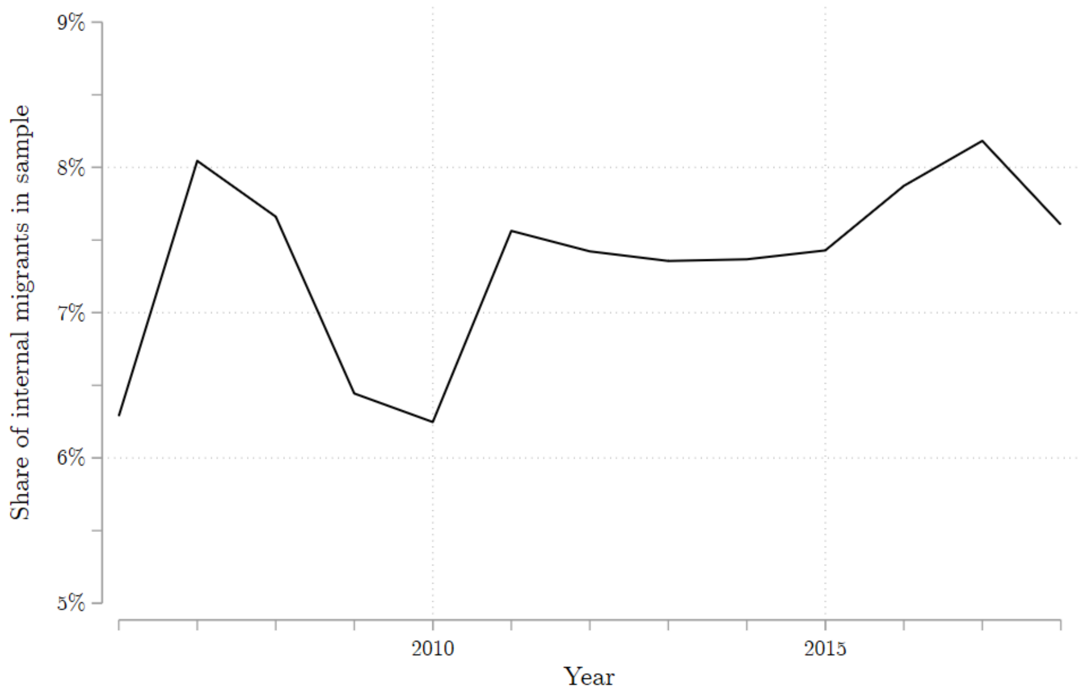
Note: Based on SOC 2000 and SOC 2010.

All monetary values are deflated using the consumer price index. Employees reported to work more than 100 hours per week, earned less than £50, more than £100,000 per week or tripled their earnings from one year to another were removed as outliers. Those switching from working full-time to part-time or vice versa were also not considered, as this might distort earnings growth. As observations are aggregated below the regional level, observations have not been weighted (following Gibbons et al., 2014).

Figure 2.1 provides the share of internal migrants in the sample each year. Each year, around 7.5% of employees move to a different TTWA. As is commonly observed in the literature, internal migrations declined during the recession in 2009 and 2010, but picked up again thereafter.

Table 2.2 compares internal migrants identified on ASHE against the full sample. Migrants earn slightly more, but also work longer hours than non-migrants. They are more likely to be male and to be working full-time. Interestingly, among non-migrants, the share of women is 50%, although the share of men in total employment is higher (Office for National Statistics, 2018). Men may have a lower propensity to appear on ASHE as they are more likely to be self-employed and therefore not being included on ASHE (Obschonka, Schmitt-Rodermund, & Terracciano, 2014). Self-employment has risen steadily in the UK (Costa & Machin, 2017), which might explain why this was not observed in an earlier study using ASHE (Gibbons, Overman, & Resende, 2011). Internal migrants work disproportionately in higher occupations (managerial or professional), according to the NSSEC classification. Migrants tend to move repeatedly: the migrants identified in

Figure 2.1: Share of migrants in the sample



Note: Internal migrants as a share of all ASHE employees.

the data were more likely to have already moved before, confirming similar findings on Italian data (Impicciatore & Strozza, 2016). Internal migrants have fewer years of total labour market experience, calculated as the total number of years appearing on ASHE, consistent with the lower average age.

Table 2.2: Summary statistics for internal migrants and non-migrants

	Internal migrants		All	
	Mean	SD	Mean	SD
Age	38.51	12.06	40.85	12.72
Female	45%	0.5	50%	0.5
Full-time	79%	0.4	73%	0.44
With second-job	2%	0.15	2%	0.13
Gross pay	546	417	515	445
Basic weekly hours	34.25	9.68	32.83	10.06
Total weekly hours	35.37	10.38	33.98	10.79
Number of employees at place of work	18672	41453	18765	44967
Higher occupation	39%	0.49	33%	0.47
Intermediate occupation	36%	0.48	39%	0.49
Routine/ semi-routine occupation	25%	0.43	28%	0.45
Previous number of migrations	0.28	0.59	0.12	0.39
Years of labour market experience	10.7	6.79	11.6	7.3
Number of observations	146956		2165653	

Note: Averaged over 2004-2018. Number of observations refers to the total observations (individuals x years).

At the firm level, we can distinguish between migrants who move between different local units of the same enterprise, e.g. to a different office, branch or plant elsewhere in the country, and those that start working for a different firm. About a third of all internal migrants continue working for the same enterprise at a different local unit after a move. As these moves could be a potential source of bias, table 2.3 compares these internal migrants, dubbed *corporate migrants* to migrants who also change employer when moving (*independent migrants*). Unsurprisingly, employees moving within a business are more likely to work at larger firms, who are also more likely to operate from multiple locations. *Corporate* internal migrants also have higher average earnings, but earnings growth upon migrating is lower. Otherwise, the differences between the groups are small.

Table 2.3: Summary statistics for corporate and independent internal migrants

	Corporate migrants		Independent migrants	
	Mean	SD	Mean	SD
Gross pay	585.66	456.02	515.81	382.42
Gross pay (logs)	6.15	0.69	6.03	0.69
Earnings growth	3%	0.25	6%	0.4
Basic weekly hours	34.44	9.29	34.1	9.96
Total weekly hours	35.68	10.05	35.13	10.62
Urban area destination	0.73	0.44	0.74	0.44
Urban area origin	0.73	0.44	0.73	0.45
Age	40.8	12.02	36.78	11.79
Female	43%	0.5	46%	0.5
Full-time	80%	0.4	79%	0.41
With second-job	1%	0.1	3%	0.18
Previous number of migrations	0.23	0.52	0.32	0.64
Years of labour market experience	12.34	6.93	9.5	6.41
Higher occupation	38%	0.49	39%	0.49
Intermediate occupation	38%	0.48	34%	0.47
Routine/ semi-routine occupation	24%	0.43	26%	0.44
Large firm (>employees)	0.9	0.31	0.73	0.44
Number of employees at place of work	28263.7	50919.12	11040.66	29851.99
Number of observations	63387		83569	

Note: Averaged over 2004-2018. Corporate migrants stay with the same enterprise when moving to another TTWA, while independent migrants start working for another enterprise when moving. Number of observations refers to the total observations (individuals x years).

2.3.2 Estimation strategy

From the theoretical framework described in section 2.2.3, we can derive an estimation strategy that relates earnings to in- and out-migration in the local area. The estimating equation is provided by equation 2.6, where w_{it} are log gross weekly earnings of individual i in year t. im_{at} and om_{at} are internal in- and out-migrants arriving in or leaving area a, where individual i works in year t, d_a is an area dummy and d_t is a year dummy to control for macroeconomic shocks. Migrants are measured as a share of total employment in area a.

$$w_{it} = \beta X_{it} + \gamma_1 im_{at} + \gamma_2 om_{at} + d_a + d_t + u_{iat} \tag{2.6}$$

There are obvious endogeneity concerns with this equation. Both internal in- and out-migration and local earnings growth might be driven by other underlying factors, for example, the opening of new businesses or plants in the area, or conversely the closure of businesses and loss of jobs. Furthermore, internal migration may be correlated with other shocks to the labour force, e.g. change in participation or immigration from abroad. The following descriptive analysis of the data in section 2.4.1 will attempt to dispel these concerns to some extent. It is very hard to predict internal migrations, both the event and the destination (Piras, 2021). Most employees do not move in any given year. Most internal migrants do experience income growth upon migration, but others do not. As the discussion of the literature on family migration has shown, there are many reasons why people move, and some of these moves may be out of career considerations for some household members, but this is not always the case. Moves, especially across larger distances, are important life decisions, where income plays an important, but not the only role. I will argue that internal migrations are therefore somewhat exogenous to other local income shocks.

2.4.Results

2.4.1 Descriptive analysis

As discussed earlier, there are large earnings disparities across the regions of the UK. Before going into the internal migration flows, I briefly describe these disparities with the data at hand. Figure 2.2 provides snapshots of average TTWA earnings in 2005 and

2018. Two findings stand out from the maps. First, there is the broad North-South divide described above. Second is the relative lack of movement between 2005 and 2018. While the highest concentration of high-earning areas can be found in the south of England, the divide can also be interpreted as urban-rural rather than North-South. The high earning areas in dark red stretch from London to Bristol in the West and up to Birmingham. However, the coastal areas of the South East, East and South West are much poorer than the urban core. By 2018, areas with relatively high earnings also include the larger cities of the North East and North West, as well as Edinburgh and Aberdeen in Scotland.

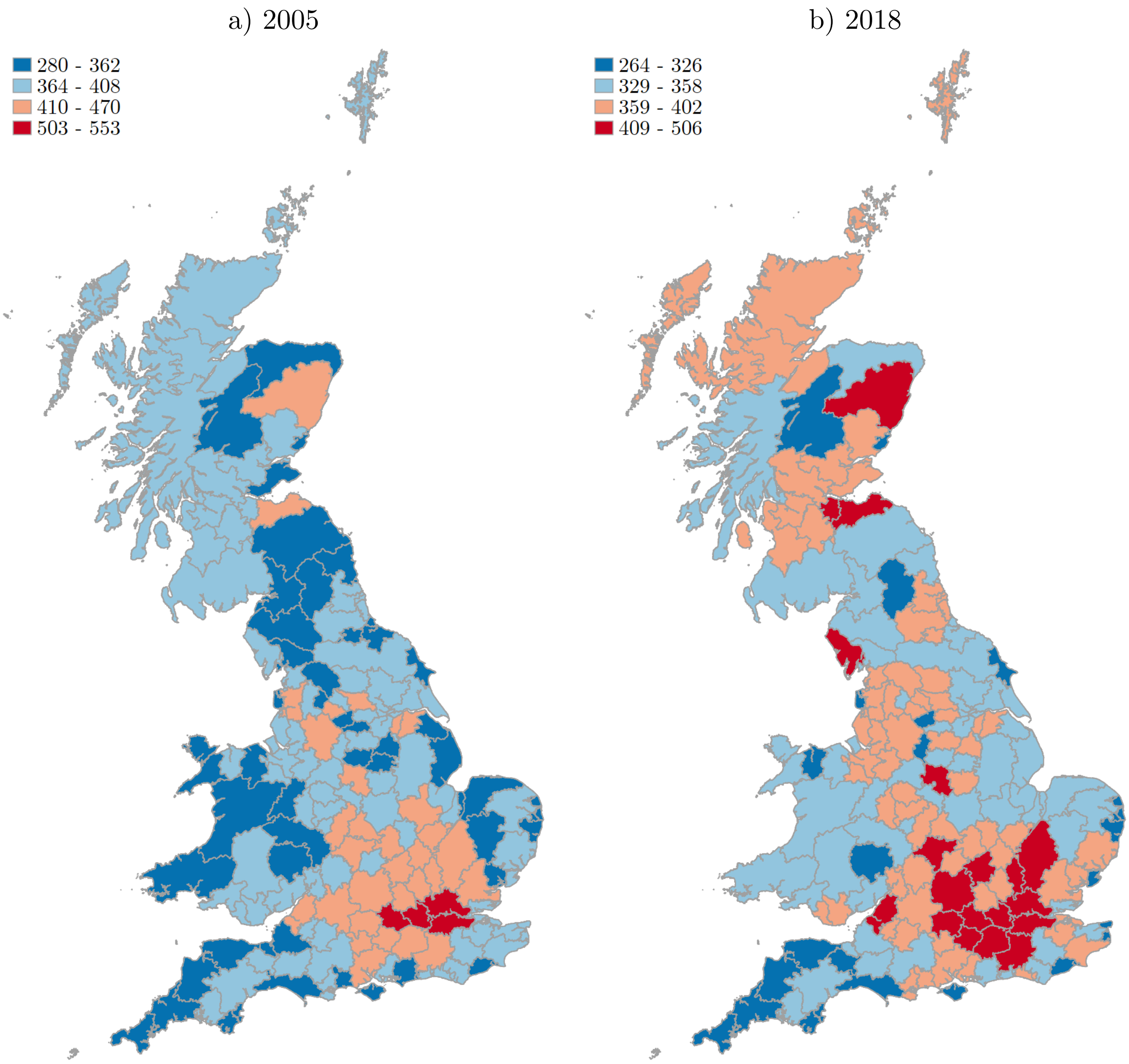
The large disparities in regional earnings are partly driven by differences in the industry and skill distribution across regions. However, as figure 2.3 shows, there is a large unexplained share that cannot be accounted for by observable differences. The map is based on residuals derived from a regression of individual log earnings on industry (broad letter-code categories), occupation, working hours, age, gender and labour market experience. Full regression results can be found in table 2.A.1 in the appendix. The map in figure 2.3 shows that regional differences persist even after controlling for these factors, and if anything become more marked. In Scotland, Aberdeen stands out as the centre of the North Sea oil industry.

Figure 2.4 depicts the patterns of net migration and total employment growth in Great Britain between 2006 and 2018. Migration flows are broadly consistent with employment growth, although smaller in magnitude, confirming that internal migration is an important contributor to employment growth, next to labour force participation, natural change, graduate mobility, and international migration. Note that ASHE is a random 1% sample, so numbers in figure 2.4 can be read as approximately one-hundredth of the total change in the employee population. Hence, internal migrants may have a significant impact to local earnings through the labour supply channel, as assumed by equation 2.4.

There is no clear pattern of net internal migration, but some comparisons with the earnings distribution can be made: London and its immediate surroundings, as well as larger cities in the North such as Manchester and Leeds are more prosperous and also received more internal migrants. However, lots of areas outside the high earning hotspots also received lots of internal migrants, and some of the high-earning areas around London lost workers due to internal migration. This suggests that earnings are only one among many factors determining migration decisions.

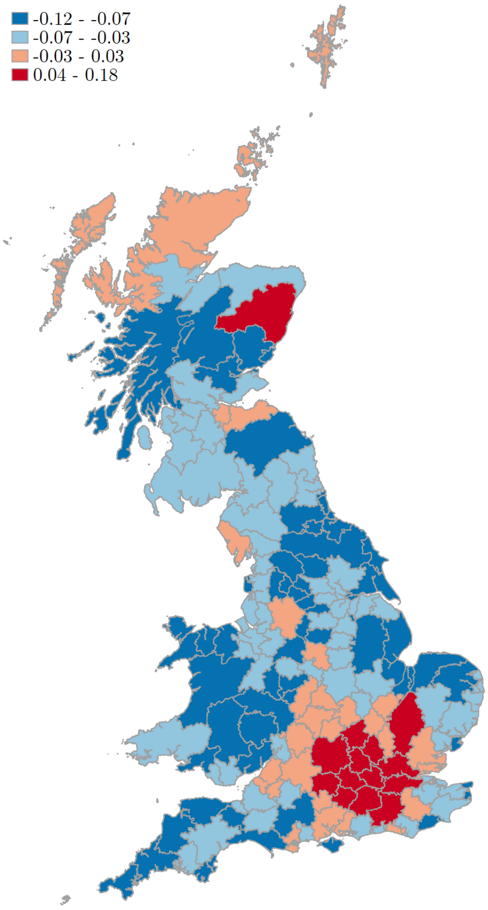
Strong employment growth in the London TTWA observed is contrary to findings

Figure 2.2: Average gross weekly earnings by TTWA



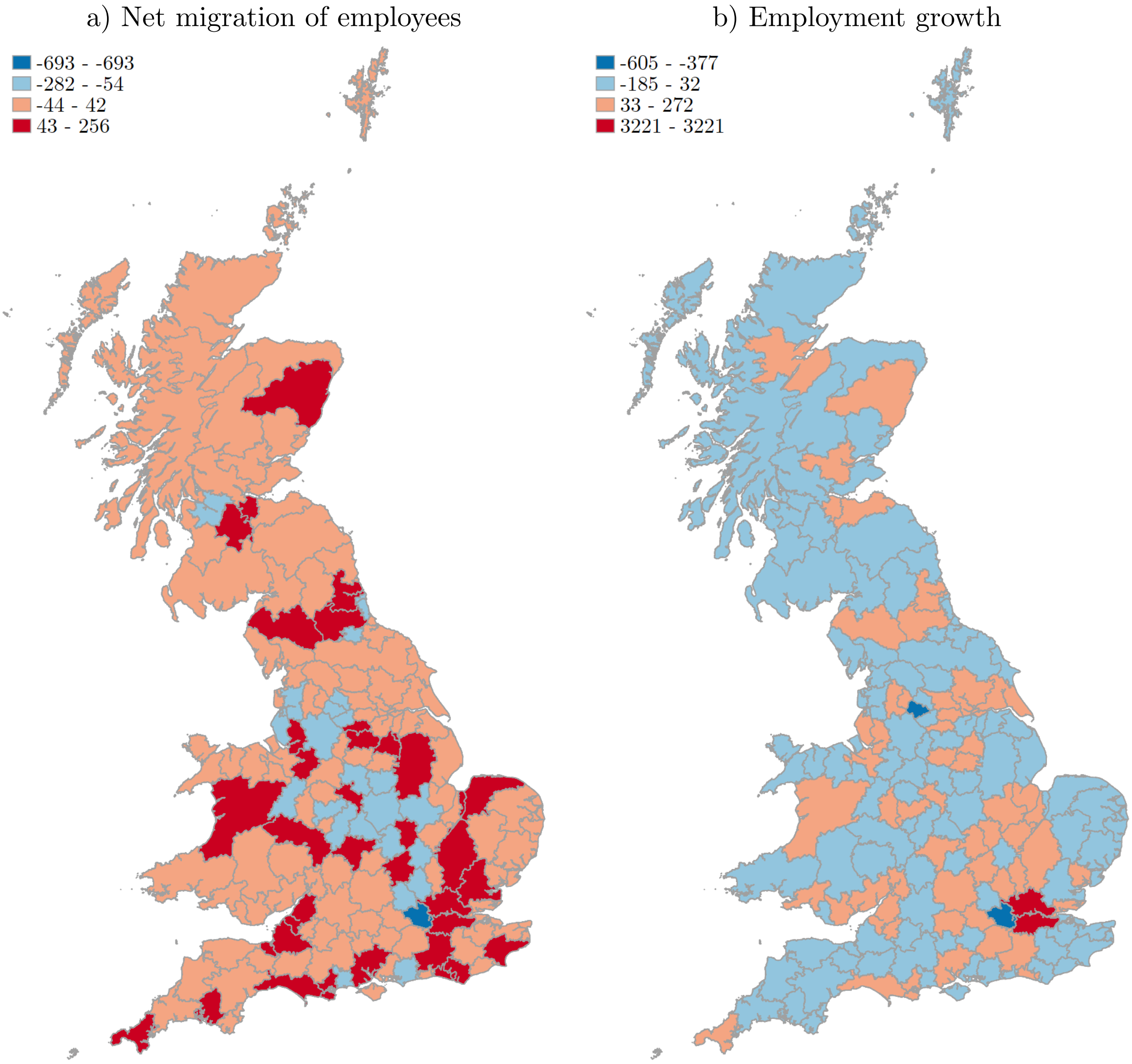
Note: Based on average log earnings, deflated using GDP deflator. Includes part-time and full-time employees. Brackets determined using k-means partition cluster analysis.

Figure 2.3: Residual earnings by TTWA



Note: Residual earnings based on regression of log gross weekly earnings on personal characteristics, year and industry dummies. Underlying regression results can be found in table 2.A.1. Brackets determined using k-means partition cluster analysis.

Figure 2.4: Employment growth and net internal migration of employees between 2006 and 2018



Note: Employment growth is calculated as the difference in the number of employees on ASHE between 2005 and 2018. Net migration is calculated as the difference between internal migrants into and out of the TTWA between 2004 and 2018. Brackets determined using k-means partition cluster analysis.

that show net outflows from London and other large cities (e.g. Champion and Coombes (2007), or ONS, Population Estimates 2018 for more recent figures). There are a number of potential explanations for this discrepancy. The most likely one is that ASHE only includes employees, and the people moving out of London are less likely to be employed, such as families with children and retirees. The definition of London provides another explanation. While TTWAs are designed so that at least 75% of workers also live there, that leaves considerable scope for people to commute in from further away. If people move out of London but continue working there, this would not be picked up in the definition of internal migrants used here. Conversely, if they take up a job in London and continue living in Cambridge, say, this would show up as a move to London.

While the aim of the chapter is to estimate the effect of internal migrants on the earnings of those who do not move, in the following I briefly consider the effect of migration on the migrants themselves. This is to get an understanding of their likely motivations and characteristics. Overall, the data show a positive correlation between internal migration and earnings growth. A move may be necessary to take up a job offer, so that career and mobility choices are linked. It might be more attractive to move for younger workers, who face a steeper career ladder and are set to gain more from being mobile (Amior, 2019). This is reflected in the younger average age of migrants. Table 2.4 confirms the positive effect of internal migration on individual earnings. It shows results of the regression of earnings growth on two dummy variables, indicating whether the individual moved in the current year, or in the last one to three years, or whether they changed jobs but stayed in the same TTWA. The job change dummy is equal to one also for non-migrants, who change jobs within the same TTWA. Individual characteristics are also included in the regressions. In the first four specifications, only the internal migration, but not the job-change dummy is included. The effect of internal migration on earnings is estimated to be positive and significant in the year of migration, and after two and three years. When the job change dummy is included, the internal migration coefficient drops, and is only statistically significant in the first year of migration. In contrast, the job change has a significant effect on earnings for all three years after it occurred. These findings suggest that the earnings effects of internal migration are mostly related to a job change, but not necessarily to the move. This adds further evidence that internal migrants are not necessarily only driven by earnings considerations.

The extend of earnings growth associated with internal migration also depends on

Table 2.4: Effect of internal migration on earnings

	Dependent variable: Annual growth rate of log gross weekly earnings							
Lag	0	1	2	3	0	1	2	3
Migration	0.011***	-0.0011	0.0022*	0.0022*	0.0076***	-0.0024**	0.0013	0.0012
	(0.00088)	(0.00083)	(0.00097)	(0.0010)	(0.00093)	(0.00086)	(0.0010)	(0.0011)
Job change					0.0098***	0.0056***	0.0036**	0.0045***
					(0.00091)	(0.00099)	(0.0012)	(0.0013)
Age	-0.0016***	-0.0012***	-0.0011***	-0.00090***	-0.0016***	-0.0012***	-0.0011***	-0.00090***
	(0.000023)	(0.000022)	(0.000026)	(0.000029)	(0.000023)	(0.000022)	(0.000026)	(0.000029)
Female	0.0081***	0.0059***	0.0081***	0.0084***	0.0081***	0.0058***	0.0081***	0.0083***
	(0.00048)	(0.00045)	(0.00053)	(0.00057)	(0.00048)	(0.00045)	(0.00053)	(0.00057)
Full-time	-0.16***	-0.18***	-0.16***	-0.15***	-0.16***	-0.18***	-0.16***	-0.15***
	(0.00086)	(0.00084)	(0.00098)	(0.0011)	(0.00086)	(0.00084)	(0.00098)	(0.0011)
2nd job	0.070***	0.047***	0.056***	0.055***	0.068***	0.047***	0.056***	0.055***
	(0.0016)	(0.0016)	(0.0018)	(0.0019)	(0.0016)	(0.0016)	(0.0018)	(0.0019)
Hours (logs)	0.20***	0.24***	0.21***	0.20***	0.20***	0.24***	0.21***	0.20***
	(0.00091)	(0.00089)	(0.0011)	(0.0012)	(0.00091)	(0.00089)	(0.0011)	(0.0012)
Higher occ.	0.012***	0.015***	0.014***	0.013***	0.012***	0.015***	0.014***	0.013***
	(0.00052)	(0.00049)	(0.00056)	(0.00060)	(0.00052)	(0.00049)	(0.00056)	(0.00060)
Routine	-0.0027***	-0.010***	-0.0056***	-0.0051***	-0.0027***	-0.010***	-0.0056***	-0.0051***
	(0.00057)	(0.00054)	(0.00063)	(0.00069)	(0.00057)	(0.00054)	(0.00063)	(0.00069)
Experience	-0.0020***	-0.0017***	-0.0014***	-0.0012***	-0.0020***	-0.0017***	-0.0014***	-0.0012***
	(0.000043)	(0.000040)	(0.000046)	(0.000050)	(0.000043)	(0.000040)	(0.000046)	(0.000050)
Employer size	0.00074***	0.00065***	0.00036***	0.00030**	0.00079***	0.00067***	0.00037***	0.00031**
	(0.000078)	(0.000073)	(0.000086)	(0.000094)	(0.000078)	(0.000073)	(0.000086)	(0.000094)
Constant	-0.48***	-0.59***	-0.55***	-0.54***	-0.48***	-0.59***	-0.55***	-0.54***
	(0.0044)	(0.0042)	(0.0050)	(0.0055)	(0.0044)	(0.0042)	(0.0050)	(0.0055)
N	1359369	1175981	850880	700416	1359369	1175981	850880	700416
R^2	0.054	0.072	0.057	0.053	0.054	0.072	0.057	0.053
Adjusted R^2	0.054	0.072	0.057	0.053	0.054	0.072	0.057	0.053

* p <0.1, ** p <0.05, *** p <0.01.

Note: The lag refers to the time lag of migration and job change, so the effect of internal migration and job change is estimated in the year of the event, and 1 to 3 years thereafter. Second job is a dummy equal to one for workers who have a second job. Hours defined as average total hours worked per week, in logs. Experience is measured as the number of years appearing on ASHE. Employer size measured as number of employees at place of work in logs. Routine is a dummy variable for routine or semi-routine occupations. Year and sector dummies included.

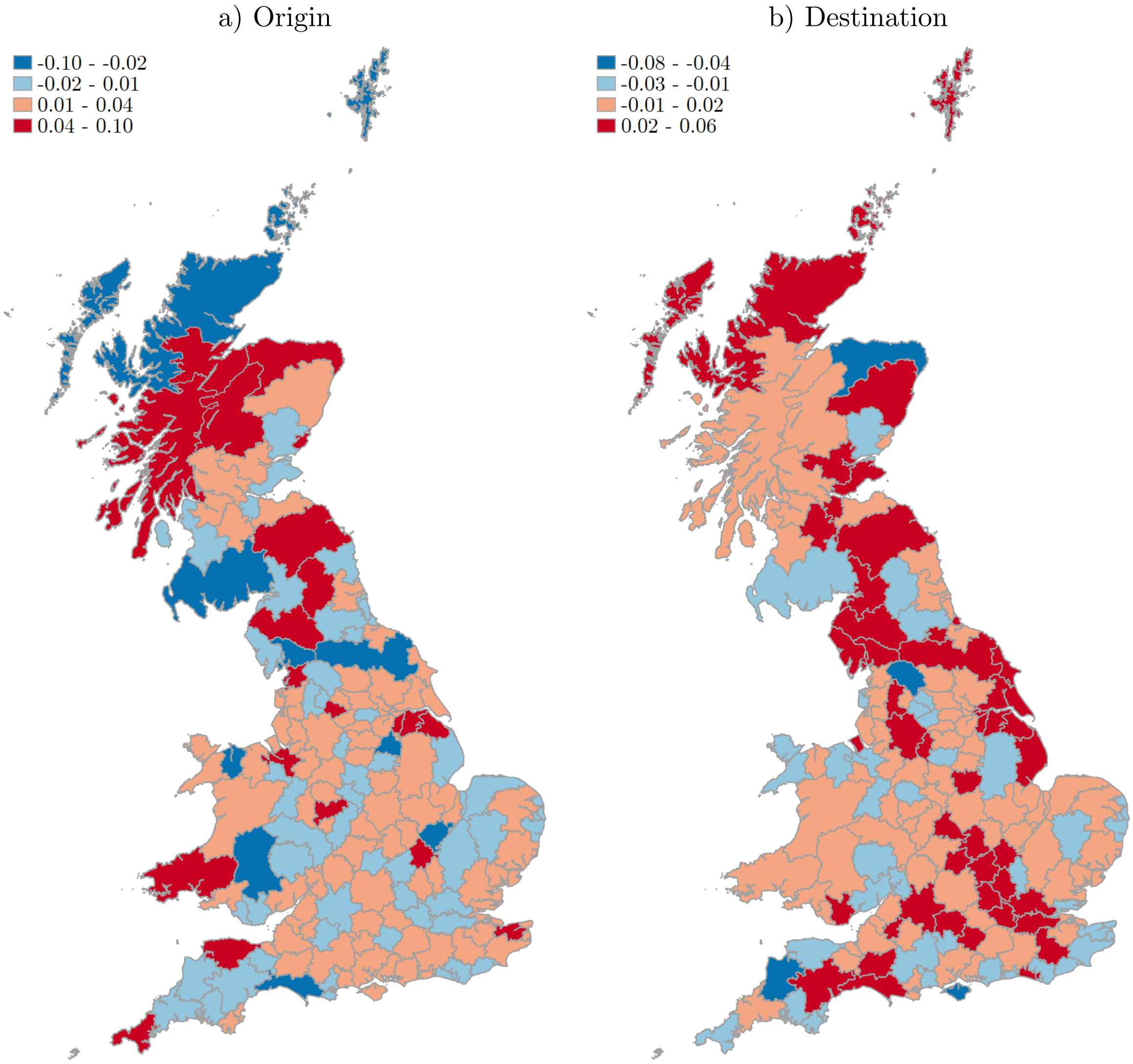
origin and destination, as figure 2.5 shows. The map on the left shows residual earnings growth for internal migrants by their origin, after controlling for personal characteristics. There is no clear pattern emerging. Internal migrants who are leaving London and the South East tend to have lower earnings growth, but the same is true of internal migrants leaving the North East. The picture is clearer in the map on the right-hand side, depicting earnings growth of internal migrants by their destination. Earnings growth is strong for those moving to London and the areas to the west. However, it is lower or even negative for internal migrants moving to the coastal areas in the south and east of London, despite high levels of migration into those areas. There is also strongly positive earnings growth for internal migrants to Yorkshire and the Humber, as well as the North West, but overall migration into those areas is relatively low.

Figure 2.5 sums up the complex picture emerging of the determinants and motivations for internal migration. Some migration and destination decisions may be driven by earnings considerations, but others are clearly not. While most internal migrants earn a return on their move, others do not. Moreover, some internal migrants increase their earnings despite moving to an area with overall quite low and stagnating earnings. In the next section, I present estimates of the effects of internal migrants on the earnings of non-migrants in the areas they leave behind and join. The evidence presented in this section gives some support to the assumption that internal migrations are exogenous to other shocks to local earnings.

2.4.2 The effect of internal migration on local earnings

I now turn to estimating equation 2.6 on the effect of internal in- and out-migrants on the earnings of non-migrants. The estimation sample includes only individuals who are not moving. I estimate equation 2.6 on three different dependent variables: log gross weekly earnings in year t, earnings growth between t and $t+1$ and earnings growth between t and $t+3$. Earnings growth rates are computed as the log differences in gross weekly earnings between those time periods. For the estimations on growth rates, only employees are included who work in the same TTWA between $t-1$ and $t+1$ or $t+3$, respectively. The internal migration variables are internal in-migrants, who move to the TTWA between $t-1$ and t and internal out-migrants, who leave the TTWA between $t-1$ and t, measured as shares of total employment on ASHE in t. Summary statistics for the estimation sample are provided in table 2.5.

Figure 2.5: Conditional earnings growth of internal migrants by origin and destination



Note: Earnings growth of internal migrants by TTWA of origin and destination. Averaged over 2006-2018. Based on regression results in table 2.4, specification with zero lag. Brackets determined using k-means partition cluster analysis.

Table 2.5: Regression summary statistics

	All	
	Mean	SD
Log gross weekly earnings	5.99	0.73
Earnings growth (t to t+1)	2%	0.22
Earnings growth (t to t+3)	5%	0.25
Share of in-migrants	0.07	0.03
Share of out-migrants	0.07	0.03
Share of in-migrants over last 3 years	0.27	0.08
Share of in-migrants over last 5 years	0.4	0.12
Share of out-migrants over last 3 years	0.28	0.09
Share of out-migrants over last 5 years	0.42	0.12
Age	40.63	12.58
Female	49%	0.5
Full-time	74%	0.44
With second-job	2%	0.14
Total hours (logs)	3.47	0.41
Higher occupation	29%	0.45
Routine/ semi-routine occupation	24%	0.43
Previously migrated	18%	0.54
Years of labour market experience	11.04	6.88
Employer size	7.07	3.03
TTWA employment (logs)	8.39	2.11
Number of observations	706966	

Note: The sample includes only employees who do not move in a given year. In- and out-migrant shares measured at the TTWA level. Second job is a dummy equal to one for workers who have a second job. Hours defined as average total hours worked per week, in logs.

Baseline estimation results are presented in table 2.6. The regressions include individual characteristics including age, gender, and job characteristics. The model is saturated with TTWA and year fixed effects. TTWA fixed effects control for structural differences between regions that do not change over the estimation period. In the absence of local price indices and measures of amenities, they also control for these factors. For example, it is well known that costs of living in the South, particularly London, are higher than in the North due to higher housing costs. TTWA fixed effects strip out these differences in levels, but they cannot control for differences in trajectories. The fixed effects can also control for amenities, particularly natural amenities that might attract people to those areas, but do not change much over time. Year fixed effects can control for common macroeconomic shocks that affect the whole country.

For each of the dependent variables, table 2.6 presents estimation results without individual fixed effects in the first three columns and estimations including individual fixed effects in the last three columns. In addition to TTWA and year fixed effects, individual fixed effects can control for unobserved personal characteristics that do not change over time, such as ability and education. The effect of the internal in-migrant share shows an interesting time pattern. Focussing on the results without individual fixed effects first, the in-migrant share has a statistically significant negative contemporaneous effect. However, the effect is economically quite small: an increase in the internal in-migrant share by one percentage point is estimated to result in 0.12% lower earnings for non-migrants. The sign of the in-migrant share coefficient turns when estimating the effect on earnings growth, although it is statistically insignificant for the 1-year and 3-year earnings growth variables.

The picture is similar when individual fixed effects are included in the last three specifications. The negative contemporaneous effect is slightly smaller. The positive effect on earnings growth over three years becomes statistically significant and larger in magnitude. These estimates are preferable to the ones without individual fixed effects, as any unobservable personal characteristics, that may be related to self-selection into an area, and therefore correlated with internal migrant flows, are controlled for.

Both the negative contemporaneous effect of internal in-migrants and the positive effect on three-year earnings growth are consistent with the model presented in section 2.2.3. In the short-run, an increase in labour supply puts downward pressure on wages, as predicted by equation 2.4. However, over the longer run, internal migrants contribute to productivity growth, and earnings increase again. In equilibrium, the wage depends no longer on labour supply but on TFP, as shown in equation 2.5. In-migrants may affect productivity, which explains the positive coefficient on the three-year earnings growth rate. The underlying mechanism explaining the link between migration and productivity is agglomeration economies (Duranton & Puga, 2004).

Note that the coefficient on the out-migrant share is never significant and flips sign frequently. This suggests that the productivity channel works through knowledge exchange and networks, rather than the skills embodied in employees. Incoming internal migrants bring new knowledge and experience from their previous place of work that they can share with their new colleagues, supporting productivity growth. This new knowledge then stays in the area. There is no evidence that out-migration has any effects on earnings, so it does not look like departing internal migrants deplete the knowledge base in the area they are leaving.

The contemporaneous negative effect of in-migration alleviates some concerns that internal migration is endogenous. If higher earnings growth in an area was a pull-factor for internal migrants, we would expect a positive correlation between in-migration and earnings, and a negative correlation between out-migration and earnings. There is no evidence for this in the regressions. It is harder to think of underlying negative shocks to earnings driving an increase in in-migration.

If knowledge sharing and networks are an important mechanism through which internal migrants affect earnings growth, it is expected that the effects are stronger in cities, as denser labour markets are more conducive to these sorts of knowledge flows (De la Roca & Puga, 2017; Glaeser & Maré, 2001; Storper & Venables, 2004). Table 2.7 tests for differences of effects in urban and non-urban areas.

TTWAs are classified as urban if they consisted mainly of urban or suburban local areas at the 2011 census. Table 2.7 shows the contemporaneous and three year growth effects in urban and non-urban areas. Individual fixed effects are included in all specifications. The pattern observed before only holds for the urban samples. In the year of the internal in-migration shock, the coefficient is statistically significant and negative, and for the three-year earnings growth rate, it is statistically significant and positive. The contemporaneous negative effect is slightly smaller in the urban sample. However, the positive effect on the three-year growth rate is 1.5-times larger. A one percentage point increase in the migrant share increases earnings by 0.075% over three years. In the non-urban sample, both coefficients are statistically insignificant and smaller in magnitude, although they retain

Table 2.6: Baseline results: effect of internal in- and out-migration on local earnings

Dependent variable	Log-level	1-y.growth	3-y.growth	Log-level	1-y.growth	3-y.growth
In-migrant share	-0.12***	0.011	0.034	-0.078***	0.0049	0.049*
	(0.030)	(0.018)	(0.029)	(0.013)	(0.016)	(0.022)
Out-migrant share	0.031	0.0021	-0.0053	-0.020	0.0027	-0.0018
	(0.023)	(0.014)	(0.021)	(0.011)	(0.014)	(0.019)
Age	0.0011***	-0.0015***	-0.0035***	-0.0045***	-0.00026	0.00015
	(0.000078)	(0.000026)	(0.000098)	(0.00045)	(0.00053)	(0.00088)
Female	-0.14***	-0.013***	-0.014***	-0.021*	-0.021*	0.0012
	(0.0020)	(0.00047)	(0.00078)	(0.0095)	(0.0095)	(0.014)
Full-time	0.27***	0.15***	0.21***	0.15***	0.30***	0.40***
	(0.018)	(0.0020)	(0.0026)	(0.0022)	(0.0028)	(0.0074)
With second-job	-0.034***	-0.022***	-0.016***	0.0049*	-0.015***	-0.011*
	(0.0066)	(0.0017)	(0.0046)	(0.0022)	(0.0031)	(0.0053)
Total hours (logs)	0.82***	-0.22***	-0.30***	0.86***	-0.52***	-0.75***
	(0.010)	(0.0024)	(0.0039)	(0.0031)	(0.0037)	(0.0066)
Higher occ.	0.47***	-0.011***	-0.0081**	0.11***	-0.0074***	-0.017***
	(0.0098)	(0.00080)	(0.0025)	(0.0012)	(0.00092)	(0.0017)
Routine occ.	-0.20***	0.0043***	0.0063***	-0.064***	0.0050***	0.014***
	(0.010)	(0.00057)	(0.0011)	(0.0010)	(0.0010)	(0.0019)
Previous migrations	0.023***	0.000046	0.00063	0.024***	0.0060***	0.0054
	(0.0034)	(0.00032)	(0.00074)	(0.00091)	(0.00086)	(0.0028)
Experience	0.016***	-0.00042***	-0.0018***	0.0014***	-0.0065***	-0.020***
	(0.00035)	(0.000088)	(0.00019)	(0.00038)	(0.00046)	(0.0020)
Employer size	0.0069***	-0.00014*	-0.0012***	0.0078***	-0.0017***	-0.0047***
	(0.00049)	(0.000065)	(0.00014)	(0.00026)	(0.00029)	(0.00073)
Constant	2.68***	0.76***	1.18***	2.90***	1.75***	2.77***
	(0.021)	(0.0085)	(0.012)	(0.031)	(0.038)	(0.071)
Individual FE				√	√	√
TTWA FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
N	1724431	1141904	580281	1724431	1141904	580281
R^2	0.73	0.065	0.13	0.60	0.13	0.20
Adjusted R^2	0.73	0.065	0.13	0.60	0.13	0.20

* p <0.1, ** p <0.05, *** p <0.01.

Note: Sample: non-internal migrants. Dependent variable: log gross weekly earnings. Earnings growth measured between t and t+n. Internal migrants moved between t and t-1 and are measured as the share of total employees in t. Experience is measured as the number of years appearing on ASHE. Employer size measured as number of employees at place of work in logs. Routine is a dummy variable for routine or semi-routine occupations.

the same signs.

Table 2.7: Regression results for urban and non-urban areas

Dependent variable	Log-level earnings		3-year earnings growth	
Urban/ rural	Urban	Non-urban	Urban	Non-urban
In-migrant share	-0.11***	-0.023	0.075**	0.0044
	(0.017)	(0.021)	(0.028)	(0.038)
Out-migrant share	-0.024	0.021	0.020	-0.049
	(0.013)	(0.019)	(0.023)	(0.034)
Individual characteristics	√	√	√	√
Individual FE	√	√	√	√
TTWA FE	√	√	√	√
Year FE	√	√	√	√
Number of observation	1298366	426065	434577	145704
R^2	0.59	0.60	0.19	0.22
Adjusted R^2	0.59	0.60	0.19	0.22

* p <0.1, ** p <0.05, *** p <0.01.

Note: Sample: non-internal migrants, separately by whether they work in predominantly urban or rural areas. Dependent variable: log gross weekly earnings. Internal migrants moved between t and t-1 and are measured as the share of total employees in t. Other independent variables included as in table 2.6, as well as year and TTWA dummies. Full regression results including all control variables can be found in table 2.A.2 in the appendix.

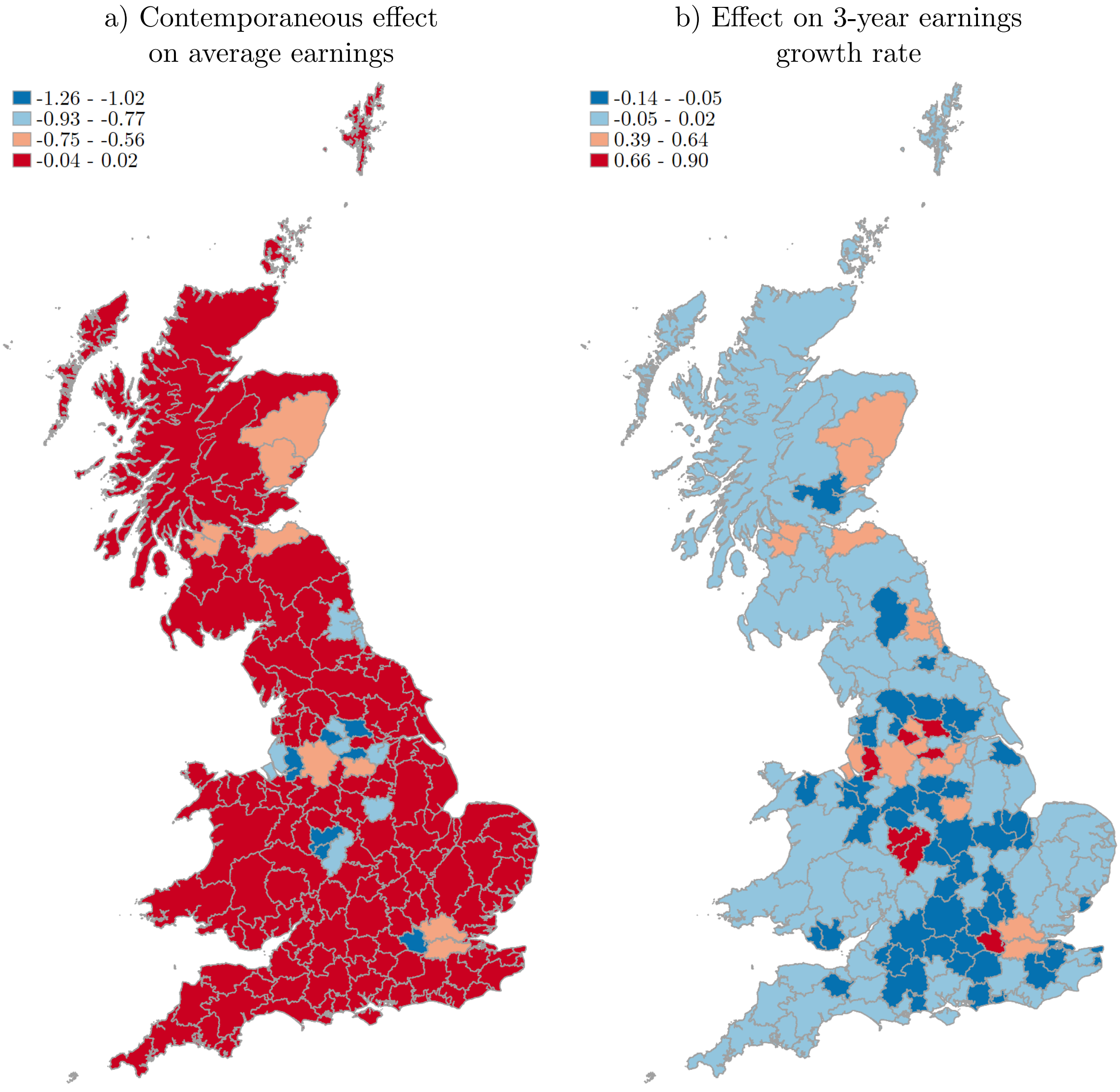
2.4.3 Evaluating the local impact

The regression coefficients together with the actual internal in- and out-migrant shares can be used to estimate the effect on earnings by TTWA. This is done in figure 2.6, by multiplying the average share of in- and out-migrants by the coefficients estimated in table 2.7, for the urban and non-urban samples separately. Note that these are the average annual effects, not the cumulative effect over the period, so the magnitudes are relatively small. The maps include the total effect from internal in- and out-migration, although the coefficients on out-migrants are statistically insignificant.

The map on the left-hand side shows the effects on log-level earnings in the year of the internal migration shock. In most areas of the country, the effect is very small, indicated by the dark red colour. Effects can be seen in London and Slough, but not the rest of the South East and East areas. Other larger areas are also affected, including Birmingham, the cities of the North West, and Newcastle. Note that these effects are not driven by the absolute size of these areas, as migration is measured in shares of total employment.

The map on the right-hand side depicts the longer-term effects on three-year earnings growth. Here, the picture reverses. The areas in the East Midlands and South West that did not receive many internal migrants had lower earnings growth. Here, the scale should be read in percentage points of the three-year growth rate. Blue shades indicate a reduction in the three-year earnings growth rate of up to 0.14 percentage points, while dark red indicates an increase in the growth rate of up to 0.9 percentage points. Among the areas benefiting the most from internal in-migration are London and Slough, as well as Birmingham, and the cities of the North West and west Yorkshire. In most peripheral areas, the effects are close to zero. The areas that are most negatively affected can be found in the areas between large urban centres in the South West, Midlands and Yorkshire.

Figure 2.6: Evaluating estimated effects at TTWA level



Note: Both figures show the average in- and out-migrant share multiplied by the regression coefficient in table 2.7, using the specifications including individual fixed effects. The scale on the left-hand side is in percent, while the scale on the right-hand side is in percentage points.

2.5. Discussion and conclusion

The chapter has considered the effects of internal migration on regional income inequality in Great Britain. While employees are relatively mobile, it is not the case that workers move exclusively to areas with high earnings prospects. To the contrary, in many areas, in particular the more rural and peripheral, employees earn on average less than before they moved. Unfortunately, those areas also benefit less from internal migration, as the positive earnings growth effect on in-migration is concentrated in urban areas.

From a policy perspective, internal migration can be a double-edged sword. Local economic development policies often create jobs that are filled by internal migrants that did not previously live in the area (Bartik, 1993). This may create the impression that these policies do not actually benefit the target population. However, the results presented here show that areas receiving in-migrants can benefit from earnings growth.

The results also show that there are adjustment costs to an internal migration shock in the form of a negative short-term effect on earnings. There may be other adjustment costs, such as increasing house prices and pressure on local services. This may pose a barrier to mobility, as local residents oppose development of housing to accommodate in-migration. Given that migrants tend to earn above-average wages, gentrification may be of concern. While housing-led development in itself may not lead to growth or more opportunities for the most disadvantaged (Rodríguez-Pose & Storper, 2020), the results in this chapter show that long-term earnings growth may be dampened in urban areas in particular that have high barriers to in-migration. Future research should consider differences in the effects of internal migration on different income groups. Evidence on the decline of the urban wage premium for those without university education suggests that those benefiting most from inflows of migrants may be higher skilled (Autor, 2019; Giannone, 2018).

The lack of an effect in rural and intermediate areas is concerning, as many of these areas are among the most deprived. The findings suggest that encouraging in-migration does not provide growth opportunities for these areas. Future research should consider why this is the case. It is possible that selection plays a role, whereby the least productive workers choose to move to non-urban areas. On the other hand, opportunities to interact and learn from new arrivals may be limited in less dense areas. A better understanding of the mechanisms behind the positive effect in urban areas is therefore also warranted. Duranton and Puga (2004) distinguish between the sharing, matching and learning mechanism as the sources of agglomeration economies. In-migrants may contribute to economies of scale, have skills that allow all employees in an area to find a job better suited to their skills, or bring new knowledge to a region that they can share with others. Groot et al. (2014) provide evidence for the Netherlands that these effects materialise particularly within specialised industries, or through Marshall-Arrow-Romer externalities, rather than between a diverse set of industries. Less dense areas may lack the scale to have a high degree of specialisation in any particular industry (Kemeny & Storper, 2015).

Nonetheless, for the overall trajectory of regional inequality, the results are encouraging. The North East, North West, and Yorkshire have many large and mid-sized cities and towns that stand to benefit from increased in-migration. While the results presented here suggest that there are considerable migration flows in some of these areas, in particular highly qualified graduates tend to move to the South East (Faggian & McCann, 2009). Based on the results presented in this chapter, this may not be a bad thing, if some graduates eventually return to northern cities, bringing with them experience and networks. Indeed, there is some evidence of return migration (Champion, 2013). Future research could consider the effect of returning migrants in particular, who may already have networks within their destination region and may therefore be particularly effective in sharing knowledge.

This suggests that a unified framework of the drivers and effects of internal migration is required. However, in a large, regionally highly unequal country like the UK, this is likely to be more complex than in a small country like Denmark, which is considered by Mitze and Schmidt (2015) for this purpose. Over the longer term, in-migration into an area may push out previous residents, fundamentally altering the demographic make-up of an area. Internal migration also interacts with immigration, where immigrants can act both as a push and pull factor for internal migrants. To fully understand these interactions requires a dataset with a longer timer series that could be used to study these dynamics.

Appendix

2.A.Additional tables

Table 2.A.1: Determinants of earnings

Dependent variable: Log gross weekly earnings		
	Coef	SE
Age	0.0011***	0.000032
Female	-0.14***	0.00064
Full-time	0.26***	0.0011
With second-job	-0.025***	0.0022
Total hours	0.81***	0.0011
Higher occupation	0.47***	0.00071
Routine/ semi-routine occupation	-0.18***	0.00076
Years not in employment	0.0018***	0.000069
Years of labour market experience	0.014***	0.00006
Number of employees at place of work (logs)	0.0085***	0.0001
Constant	2.62***	0.0056
Number of observation	1831424	
R^2	0.72	
Adjusted R^2	0.72	

* p <0.1, ** p <0.05, *** p <0.01.

Note: Year and industry letter code dummies included. Residuals presented in figure 2.3 are derived from this regression.

Table 2.A.2: Full regression results for urban and non-urban areas

Dependent variable	Log-level earnings		3-year earnings growth	
Urban/ rural	Urban	Non-urban	Urban	Non-urban
In-migrant share	-0.11***	-0.023	0.075**	0.0044
	(0.017)	(0.021)	(0.028)	(0.038)
Out-migrant share	-0.024	0.021	0.020	-0.049
	(0.013)	(0.019)	(0.023)	(0.034)
Age	-0.0043***	-0.0044***	0.00020	-0.0024
	(0.00054)	(0.00100)	(0.00096)	(0.0024)
Female	-0.029**	-0.0014	0.0038	-0.00091
	(0.011)	(0.020)	(0.017)	(0.027)
Full-time	0.15***	0.12***	0.40***	0.41***
	(0.0025)	(0.0047)	(0.0086)	(0.015)
With second job	0.0059*	0.0057	-0.013*	-0.0060
	(0.0025)	(0.0040)	(0.0063)	(0.010)
Total hours (logs)	0.85***	0.84***	-0.75***	-0.78***
	(0.0035)	(0.0071)	(0.0078)	(0.013)
Higher occupation	0.11***	0.084***	-0.016***	-0.023***
	(0.0014)	(0.0024)	(0.0019)	(0.0035)
Routine occupation	-0.064***	-0.048***	0.018***	0.0041
	(0.0012)	(0.0019)	(0.0022)	(0.0036)
Previous migrations	0.025***	0.016***	0.0042	-0.0018
	(0.0011)	(0.0022)	(0.0035)	(0.0061)
Experience	0.0012**	0.0026**	-0.020***	-0.016***
	(0.00046)	(0.00081)	(0.0023)	(0.0045)
Employer size	0.0074***	0.0087***	-0.0044***	-0.0054***
	(0.00031)	(0.00054)	(0.00086)	(0.0015)
Constant	2.91***	2.92***	2.51***	2.98***
	(0.026)	(0.061)	(0.070)	(0.12)
TTWA FE	√	√	√	√
Individual FE	√	√	√	√
Number of observation	1298366	426065	434577	145704
R^2	0.59	0.60	0.19	0.22
Adjusted R^2	0.59	0.60	0.19	0.22

* p <0.1, ** p <0.05, *** p <0.01.

Note: Sample: non-internal migrants, separately by whether they work in predominantly urban or rural areas. Dependent variable: log gross weekly earnings. Internal migrants moved between t and t-1 and are measured as the share of total employees in t. Employer size is measured as number of employees at place of work in logs. Routine occupation is a dummy for routine and semi-routine occupations. Experience is measured as the number of years appearing on ASHE.

Chapter 3

Labour market effects of industry concentration: A regional analysis of Great Britain

3.1.Introduction

Industry concentration, the degree to which industries are dominated by a small number of firms, is rising in many countries (Philippon, 2019; Ennis, Gonzaga, & Pike, 2019). This can be damaging to consumers, if prices are high and choice is restricted, but labour markets can also be negatively affected (Eeckhout, 2021). In this chapter, I estimate the effect of market power and industry concentration on average wages and labour shares in Great Britain. Industry concentration is also associated with growing regional concentration of businesses. In this context, most dominant businesses can be found in London and the wider South East, the two regions with the highest average earnings. I estimate the contribution of market power to regional income inequality. While the overall effects are small, the results are suggestive of the growing importance of dominant firms in regional economies and labour markets. The findings provide further evidence for the importance of considering the wider impact of market power, other than on consumer welfare.

Market power allows firms to charge a mark-up over cost, allowing them to earn rents, or pure profits. If wages stay constant, this means that the labour share, the share of value added earned by workers, falls. A falling labour share and a negative correlation with industry concentration have been documented extensively (Autor et al., 2020; Barkai, 2020; Berkowitz, Ma, & Nishioka, 2017; Berlingieri, Blanchenay, & Criscuolo, 2017). A falling labour share might signal increasing inequality and falling bargaining power of workers (Atkinson, 2009; Elsby, Hobijn, & Sahin, 2013; Piketty, 2014; Stansbury & Summers, 2020). However, as I will show, firms with market power pay in fact higher wages, despite a lower labour share. This is consistent with rent sharing models of the labour market (Akerlof & Yellen, 1990; Blanchflower, Oswald, & Sanfey, 1996; Van Reenen, 1996).

Some regions stand to benefit more from growing concentration than others. In particular, superstar regions that are already very productive and host many successful firms may benefit if these firms gain market power. Smaller businesses in lagging regions are more likely to be driven out of business by a dominant competitor. Growing concentration can also consolidate growth opportunities in successful cities through other channels, for example by acquisitions of firms from lagging regions (Feldman, Guy, Iammarino, & Ioramashvili, 2021) or through access to financial capital that allows young firms to jump growing barriers to entry (Martin, Berndt, Klagge, & Sunley, 2005).

To my knowledge, this is the first study to estimate the effects of market power and industry concentration for Great Britain, and to adopt an explicitly regional lens. I use a firm-level survey, the Annual Respondents Database X, spanning the years from 2002 to 2014. I find that firms with market power pay substantially higher wages, while the labour share at these firms is lower, pointing to a rent-sharing model. However, while dominant businesses are concentrated in London and the South East, the effects on regional earnings are limited in these regions, as a high number of dominant firms is offset by many small firms with little market power. Nonetheless, the results provide important insights for the interaction between competition and local development policy. As fast growing industries are highly concentrated, barriers to entry make it even harder for regions outside established clusters to foster successful businesses. In order to grow, regions need to attract investment from a small number of dominant firms, likely a zero-sum game. Local growth strategies therefore also need to take into account the competitive environment and industrial structures to establish where local firms may have a competitive advantage.

The chapter proceeds as follows: Section 3.2 discusses related literature and provides a theoretical framework for the analysis. Section 3.3 describes the data and empirical methods used. Section 3.4 provides the results. Section 3.5 discusses the results and concludes.

3.2.Related literature and theoretical framework

Declining competition is of growing concern for policy makers and researchers alike. Some prominent antitrust cases in the European Union and United States, in particular around technology platforms, have attracted public attention, but research shows that the phenomenon affects a diverse range of industries and many countries (De Loecker & Eeckhout, 2018; Philippon, 2019). Declining competition is manifested in increasing industry concentration or higher price mark-ups over cost (Autor et al., 2020; De Loecker, Eeckhout, & Unger, 2020; Grullon, Larkin, & Michaely, 2019). In the following, I will briefly discuss some of the causes of growing industry concentration. Next, I discuss the growing literature on the effect of growing concentration on wages and income inequality. In this context, recent research has considered the impact on labour shares, the share of output earned by workers. Lastly, I review related literature on the spatial dimension of industry concentration, an aspect that has received much less attention.

3.2.1 Increasing industry concentration

Industry concentration and market power

While closely aligned, market dominance is not necessarily the same as market power (Philippon, 2019). Some industries are highly concentrated and dominated by a small number of companies, but remain intensely competitive (Syverson, 2019). In the US and the UK, supermarkets are an example of this. Mark-ups are a more precise measure of market power, showing the ability of firms to set prices above marginal cost. In practice, there is a strong correlation between growing industry concentration and growing mark-ups and profits (De Loecker & Eeckhout, 2018; De Loecker et al., 2020; Eggertson, Robbins, & Getz Wold, 2018; Furman & Orszag, 2015).

The relationship between concentration and competition differs across industries. For tradable goods, markets are global, where complex relations of market power play out through global value chains (Selwyn & Leyden, 2021). For some firms and industries, the appropriate market to assess their dominance and concentration is global (Gutiérrez & Philippon, 2020). In these cases, global competition can limit market power of dominant firms. On the other hand, the market size for some retail and service businesses can have a very limited radius. In practice, competition may be more limited than national measures would imply. Business structures also play a role. The expansion of national chains may result in an increase in local competition even if the number of independent businesses falls (Hsieh & Rossi-Hansberg, 2019).

Drivers of increasing concentration

Drivers of increasing concentration can broadly be linked to technological and institutional change. In terms of technology, the growing importance of intangible assets may pose a barrier to entry. Intangible assets are an overhead cost with infinite economies of scale, imposing high entry costs for new entrants to match the productivity of incumbents (De Ridder, 2019). The declining marginal costs of such industries create natural monopolies. A special case are network industries, where the product becomes more useful as the number of users or customers increases (Crouzet & Eberly, 2019; Rochet & Tirole, 2006). Lower search and transport costs may also result in a winner-takes-most market, where consumers swiftly gravitate towards superior products, produced by the most productive firm (Autor et al., 2020; Syverson, 2019).

Institutions, and in particular competition policy or anti-trust enforcement also affect industry concentration (Covarrubias, Gutiérrez, & Philippon, 2019). In the global context, competition policy in the EU is considered to be strong, with associated lower consumer prices in many sectors (Gutiérrez & Philippon, 2019). However, the UK follows the US trajectory, with an economic model overall more aligned to American liberalism (Schneider & Paunescu, 2012). An increase in anti-competitive practices, weaker competition policy, or more barriers to entry as a result of incumbents' lobbying efforts all drive the economy-wide increase in concentration (Khan & Vaheesan, 2017; Philippon, 2019).

In many instances, the cause of increasing concentration is a combination of changing technology and institutions catching up on the changing environment. Especially in digital industries that exhibit characteristics of natural monopolies, competition policy is struggling to adapt (Argentesi et al., 2020; Bourreau & de Streel, 2019).

3.2.2 Impacts of market concentration on earnings

Competition policy is mostly concerned with consumer welfare, as firms with market power have power to raise prices above marginal costs, while a competitive market is associated with lower prices and a wider variety of choice (Khan & Vaheesan, 2017). However, market power also impacts earnings more widely. While workers may be beneficiaries of their employers' market power, concentration may also manifest itself through monopsony power, or the power of employers to set wages below the competitive level.

Efficiency wages and profit sharing

Firms with market power may be able to charge prices above marginal cost and therefore earn pure economic profits. These rents are passed on to the owners or workers of the firm. Models of rent sharing show how firms maximise profits by passing a share of rents on to workers, to attract and retain talent, discourage shirking and increase productivity (Akerlof & Yellen, 1990; Blanchflower et al., 1996; Hildreth & Oswald, 1997; Krueger & Summers, 1988). The extent of rent sharing depends on the relative power of workers and owners of capital. Empirical evidence shows that trade unions increase worker power to capture rents, resulting in a higher union wage premium for businesses with market power (Abowd & Lemieux, 1993; Stewart, 1990).

A special case that has been extensively studied is the returns to market power conferred by patent protection. As the development of new inventions may require substantial upfront investments, patents provide some protection from competition, so that inventors are able to recoup these costs. Estimates suggest that around 30% of patent rents are passed on to workers (Kline, Petkova, Williams, & Zidar, 2019; Van Reenen, 1996). However, rival innovation, resulting in increased competition in the product market, reduces this wage premium (Van Reenen, 1996).

Monopsony power

In industries where workers have little power, industry concentration exacerbates this asymmetry (Stansbury & Summers, 2020). The extend to which firms pass rents on to workers, and the overall level of wages depends on the level of competition in the labour market, or the firm's monopsony power (Kroft, Luo, Mogstad, & Setzler, 2020; Manning, 2011). Under perfect competition, wages grow at the same rate as productivity. In labour markets where firms have wage-setting power, the link between productivity and wage growth breaks. As productivity grows faster than wages, the labour share falls (Abel, Tenreyro, & Thwaites, 2018; Azar, Marinescu, Steinbaum, & Taska, 2019; Benmelech, Bergman, & Kim, 2018). Abel et al. (2018) find overall stable levels of monopsony power in the UK over the last two decades, but with substantial variation across industries. Other evidence on the increase of involuntary part-time and temporary employment over the period suggests a decline in worker bargaining power in the UK, in particular in the aftermath of the financial crisis (Green & Livanos, 2015).

In many cases, labour markets are more geographically confined than product markets, and workers' bargaining power varies regionally. Firms have less monopsony power in denser labour markets, one of the drivers of the urban wage premium (Hirsch, Jahn, Manning, & Oberfichter, 2019; Manning, 2010). Firms are able to exercise monopsony power where workers face barriers to finding or taking up a better paid job, for reasons such as preferences or barriers to mobility (Manning & Petrongolo, 2017; Benmelech et al., 2018). The effect of dominant firms can also go in the other direction. In the USA, some retailers, which employ large numbers of relatively low-skilled workers, recently implemented an internal wage floor above the statutory minimum wage. In labour markets where these employers play an important role, average wages increased also at other firms (Derenoncourt, Noelke, & Weil, 2021).

3.2.3 Labour shares and inequality

As industry concentration affects labour markets, a particular concern about growing concentration is around increasing income inequality. Growing industry concentration has been linked to a decline in the labour share (Autor et al., 2020). Additionally, in so far as firms pass on rents to workers, wages diverge between firms with more and firms with less market power.

Divergence in returns to capital and labour

Labour shares have been declining for several years in many countries around the world (Dao et al., 2017; Elsby et al., 2013; Karabarbounis & Neiman, 2013). A declining labour share is concerning because it implies a falling share of income going to workers and a rising share going to a smaller group of capital owners (Atkinson, 2009; Dao et al., 2017). Another interpretation of the declining labour share is that wages grow more slowly than labour productivity (Pessoa & Van Reenen, 2013; Schwellnus, Pak, Pionnier, & Crivellaro, 2018).

The decline of the labour share can be directly connected to growing industry concentration. Barkai (2020) constructs measures of capital costs in addition to labour costs at the industry level in the US, and finds that both have been declining as a share of total value added, with a rise in the share of pure profits. This is linked to industry concentration: as firms are able to charge a higher mark-up over production costs, profits rise. Autor et al. (2020) similarly find a link between growing industry concentration and falling labour shares using US firm-level data. They explain these findings with a model of *superstar* firms, in which larger firms are more productive and require less workers in administrative overhead occupations, which explains the declining labour share.

Others have stressed alternative factors in the global decline of the labour share, such as technological change (Dao et al., 2017; Karabarbounis & Neiman, 2013; Schwellnus et al., 2018), globalisation (Reshef & Santoni, 2019), and industrialisation in developing economies (Lewis, 1954; Maarek & Orgiazzi, 2020). Among institutional factors, declining trade union power is associated with declining labour shares (Stansbury & Summers, 2020). The labour share declined significantly in the UK following the Thatcher era and the associated decline in union power. It then grew again from the end of the 1990s (Judzik & Sala, 2013), to some extend attributable to the introduction of the national minimum wage in 1999 (Metcalf, 2008). Similarly, worker protection laws and the extend of the welfare state affect labour's bargaining power and therefore the labour share (Deakin, Malmberg, & Sarkar, 2014; Stockhammer, 2017). Yet, these national policies cannot explain local variation in the labour share, as well as a continuing decline in industries with already low union representation.

Divergence of wages between firms and industries

To reiterate, firms with market power are able to charge mark-ups over cost, earning pure profits or rents. These rents are likely to be (partially) shared with workers. This is consistent with evidence of a growing intra-industry dispersion of wages between firms (Card et al., 2013, 2018; Berlingieri et al., 2017; Song, Price, Guvenen, Bloom, & von Wachter, 2019). Dominant businesses are able to pay higher wages, while firms with less market power are not able to pay workers above their marginal product.

There is no contradiction between a firm paying relatively high wages but having a low labour share. This has further implication on inequality between workers. Rents are not passed through a firm's supply chain. In the context of growing outsourcing of labour intensive tasks, this implies that the circle of workers benefiting from rent sharing is becoming smaller and more homogenous (Goldschmidt & Schmieder, 2017). Moreover, Kline et al. (2019) find that rents from patenting benefit male workers more, as well as workers in the upper half of the firm-specific wage distribution. Comparing the monopolists of the digital era to the giants of the mechanical age, Philippon (2019, ch. 13) finds that digital firms employ on average less workers, and have less diverse workforces. This implies that a smaller and more select group of workers benefits from their market power.

3.2.4 Location of dominant firms

As discussed, businesses with market power also affect the labour market. Therefore, their presence in the local economy may play an important role for local employment and wages. Besides wide regional divides in average earnings (Martin et al., 2016), there is also evidence of considerable regional variation in labour shares (Izushi, 2008). While not the main focus of the chapter, the following briefly discusses how industries that are dominated by a small number of large firms tend to be also geographically concentrated in a few regions.

There are several mechanisms that would make an industry become more spatially concentrated. Some locations may be more likely to produce dominant firms. Urban density contributes to businesses' productivity and may allow them to grow faster and dominate an industry (Duranton & Puga, 2004; Gaubert, 2018). Access to finance and political power may be just as important and work as direct drivers of firms' ability to establish monopoly power (Feldman, Guy, & Iammarino, 2019; Philippon, 2019). The UK has a centralised financial system that impedes growth opportunities for SMEs, particularly further away from London (Klagge & Martin, 2005; Lee & Brown, 2017). Firms located further away from financial centres are also less likely to access venture capital finance (Chen, Gompers, Aovner, & Lerner, 2010; Cumming & Dai, 2010; Martin et al., 2005) and to be listed on a stock exchange (Wójcik, 2009). Venture capital is an important source of funding for high growth, innovative start-ups that might disrupt industries and challenge dominant incumbents (Gompers & Lerner, 2001). While venture capital investments have traditionally favoured London and the South East (Martin, 1989), the growing internationalisation of the industry reaffirms this regional bias, with London as a global financial centre receiving over 80% of recent foreign venture capital investments (Harrison, Yohanna, & Pierrakis, 2020).

Mergers and acquisitions may also lead to spatial concentration. Feldman et al. (2021) show how Big Tech firms concentrated in Silicon Valley acquire tech start-ups across the

United States and indeed the world, which often means that the start-up also relocates to California. Some M&A deals are structured deliberately to avoid anti-trust scrutiny, resulting in lower competition in affected markets (Kepler, Naiker, & Stewart, 2021). Mergers and acquisitions are also associated with growing concentration of businesses in centres of political power, such as state capitals (Rodríguez-Pose & Zademach, 2003). Across countries, centralisation of political power is associated with increased urban concentration (Ades & Glaeser, 1995; Kim & Law, 2012).

3.2.5 Theoretical framework

To summarise, a large literature documents the rise of market power across many countries. This allows businesses to charge mark-ups and earn rents, or pure profits. On the one hand, businesses may exercise monopsony power to pay less than market wages. On the other hand, these profits may be shared with workers. Recent empirical evidence points in the latter direction, of rent sharing as a driver of earnings inequality between firms. This affects earnings inequality both within industries – between firms with different degrees of market power – as well as between industries with different degrees of concentration. The following translates this into a simple theoretical framework relating market power to earnings and labour shares.

The analysis in this chapter does not provide a causal mechanism, but rather an accounting framework for the effects of industry concentration at the firm and regional level. Consider a firm i that produces output Y_i according to a Cobb-Douglas production function using capital K_i, labour L_i and technology A_i:

$$Y_i = A_i L_i^{\alpha} K_i^{1-\alpha} \tag{3.1}$$

Then, as appendix 3.A shows, the labour share $\frac{w_i L_i}{Y_i} = \alpha$, where w_i is the wage rate. The capital share is $\frac{r_i K_i}{Y_i} = 1 - \alpha$.

If the firm has market power, it is able to charge mark-up m_i over prices, so that total output is $(1 + m_i)Y_i$ (see, e.g. De Loecker, Eeckhout, and Mongey (2021) for a model of industry concentration and mark-ups). We assume the capital and labour markets remain competitive, but workers and shareholders can bargain over the mark-up. In particular, workers share s_i of the mark-up, while shareholders receive $1 - s_i$. The worker share is determined through negotiation. For example, Van Reenen (1996) describes a bargaining model for innovation rents, where firms bargain over wages with a union. The presence of a union is not crucial to arrive at the results. It is equally plausible that firms negotiate wages with "insider" employees that have some firm-specific skills and knowledge and therefore have some bargaining power, as worker turnover is costly for the firm. With this in mind, the labour share can be written as:

$$\tilde{LS_i} = \frac{s_i m_i Y_i + w_i L_i}{(1 + m_i) Y_i} \tag{3.2}$$

and the average wage as:

$$\tilde{w_i} = \frac{s_i m_i Y_i}{L_i} + w_i \tag{3.3}$$

For any positive share of the mark-up gained by workers, the average wage will increase. However, the labour share will only increase if $s_i > \alpha$. For $s_i < \alpha$, the labour share will fall despite growing wages.

This has several implications. On the one hand, growing heterogeneity in wages among firms would be expected, as wages at firms with market power will be higher (Song et al., 2019; Card et al., 2013). This also corresponds to the notion of *superstar* firms (Autor et al., 2020). The focus of this chapter is on the impacts of industry concentration on regional wage inequality. In particular, if there is a regional concentration of firms with market power, this will also increase regional inequality. To my knowledge, the labour market effects of dominant firms have not yet been studied in a regional context. At the regional level, the effects of dominant firms may be felt more strongly, if dominant firms are clustered. This heterogeneity across regions may not be evident when looking at the problem at an aggregate level.

3.3.Data and empirical methods

3.3.1 Data

The Office for National Statistics (ONS) collects data on GVA and employment costs through the Annual Business Survey (ABS) and its predecessor before 2008, the Annual Business Inquiry (ABI). For this study, I accessed the confidential panel of firm-level records that is made accessible as the Annual Respondents Database X (ARDX) through the Secure Research Service at the ONS. It is available from 2002 to 2014. The ABS/ ABI surveys all businesses with more than 250 employees and uses a sampling frame for smaller businesses that is stratified by size and industry. It is restricted to Great Britain and therefore does not include businesses in Northern Ireland. The survey covers approximately two-thirds of GB GDP. Important sectors that are excluded are financial intermediation and insurance (the latter is excluded only in 2013 and 2014), most parts of the agricultural sector, public administration and defence, and public provision of education and health services.

The survey is conducted at the reporting unit level, which is the smallest collection of establishments for which a company can provide financial information. Most businesses consist of a single establishment that constitutes the reporting unit. However, larger, more complex businesses have many establishments that are grouped into reporting units, for example by function or location. Businesses are sampled to take part in the survey from the universe of reporting units. Large businesses with more than 250 employees are always surveyed. Small and medium sized businesses are surveyed for two consecutive years once selected. Micro-businesses are also included in the survey but are surveyed only for one time if included in the sample. This means that there is a limited panel element to the survey: most businesses that are sampled are surveyed for at least two years. However, not all businesses respond, and businesses may cease trading after their first survey, so in practice the panel aspect is selective.

Market power is measured by a firm's share in total industry turnover. Industries are defined by SIC codes, with the 4-digit, most detailed definition used in the preferred specifications. SIC codes change over time, and some steps were undertaken to harmonise codes over time, which are detailed in appendix 3.B. My preferred measure of industry concentration is the Herfindahl-Hirschman index defined as the sum of squared market shares of the industry [1]. The higher the index, the more concentrated, or dominated by a smaller number of firms, the industry is. This indicator is used in the UK context, for example, by Abel et al. (2018) to measure market power of employers in industries defined by 2-digit SIC codes. As an alternative measure of concentration, I use concentration ratios, defined as the share of the largest four or largest twenty businesses in total industry turnover.

While businesses provide data on total wages and salaries paid during a year, they are not asked for employment figures which are required to calculate average salaries.

[1] Formally, the Herfindahl-Hirschman index is defined as $\sum_{i=1}^{N} s_i^2$, where s_i is the market share by turnover of business i in a certain industry

Instead, employment numbers are merged from the Business Registers and Employment Survey (BRES) and the Inter-departmental Business Register (IDBR). This results in several issues. Even if a business is included both on the ABS and BRES, the timing of the two surveys is different, so that the reporting periods are not the same. Employment figures from the IDBR may be interpolated for several years if no update from the business is available.

The variables used to calculate the labour share are GVA at market prices and total employment costs. These are derived in turn from several survey questions, but are provided as standard measures on the dataset. GVA at market prices is calculated as total turnover minus total purchases of goods, materials and services, adjusted for taxes paid and changes in stocks and work in progress. Total employment costs include total wages, salaries and redundancy payments, but exclude employer social security contributions. Responding businesses are requested to include compensation in cash and in kind, including any bonus payments or premiums (Office for National Statistics, n.d.). This is important, as growing popularity of equity-based compensation means that measures of the labour share are biased downward if only compensation in cash is included (Eisfeldt, Falato, & Xiaolan, 2021).

For regional analysis, matching a business to a location is straight-forward in most cases: businesses that consist of a single local unit can be matched to their postcode, and from there to any other geographical unit. However, for reporting units that consist of establishments in different locations, some mapping needs to be done. Fortunately, only few reporting units span several NUTS3 areas, the smallest geographical unit of analysis used here. Where they do, reporting units are allocated proportionally by the employment shares in the different locations. This is possible, because employment estimates are available at the local unit level from the IDBR.

The data have several shortcomings. The self-employed are not included in the survey. This is a problem, since the use of self-employed sub-contractors varies over time and across industries. Self-employment is on the rise across the UK, and there is evidence that it is most prevalent at the lower and higher ends of the pay distribution (Costa & Machin, 2017). The growing substitution of sub-contractors for employees may distort labour shares, as labour costs are shifted from employment costs into other input costs. This would bias the labour share downward and may also distort average wages, for example if lower paid work is more likely to be contracted. Furthermore, payments to directors, partners and proprietors are also not included except for regular salaries. While this should not bias the results much for larger businesses, in smaller businesses, where the boundaries between personal and business finances may be more blurred, and directors may forego a higher salary in favour of capital income for tax reasons, this may bias both wages and the labour share downward. Another shortcoming of the data is that the financial sector is not included. This sector plays an important role particularly in London and is an important driver of high average earnings there.

The survey collects a range of other variables, such as an indicator whether the business has conducted any research and development during the last year, the country of ultimate ownership, which has been converted into an indicator for non-UK ownership, and payments to employment agencies, which has been converted into the share of agency employment in total employment costs. Summary statistics for the variables used in the analysis can be found in table 3.1. The dataset contains some extreme outliers. Therefore, the sample has been trimmed by dropping the 0.1% of businesses with the highest and lowest labour shares and average wages.

3.3.2 Estimation strategy

I now turn to estimating the effect of market power and industry concentration on labour shares at the firm level. I estimate the following equation:

$$Y_{jit} = \beta_1 S_{jit} + \beta_2 HH_{it} + \beta_3 S_{jit} * HH_{it} + \beta_4 X_{jit} + \gamma_i + \tau_t + \epsilon_{jit} \tag{3.4}$$

Where Y_{jit} is the outcome variable of interest – average wages and labour shares – of firm j in industry i and year t, HH_{it} is the log Herfindahl-Hirschman in industry i in year t, S_{jit} is the market share of firm j in industry i and year t, X_{jit} are control variables at the firm level, γ_i are industry and τ_t are year fixed effects, and ϵ_{jit} is the error term.

Industry concentration can be measured at different levels of industry aggregation. In the preferred specifications, industry concentration and market shares are measured at the 4-digit industry level, with fixed effects entered at the same level. Robustness checks show that the effects remain similar for 2- and 3-digit industries.

The control variables included are log employment and log turnover, which may capture scale effects. A dummy indicates whether the firm plans to undertake any R&D in the next two years. More innovative firms may be able to achieve a dominant position by

Table 3.1: Summary statistics

Variable	Definition	Mean	SD
Labour share	Compensation of employees + employer taxes and social security contributions divided by GVA	0.553	0.258
Average wage (th£)	Wages and salaries divided by total employment	33.64	357.3
Average wages (logs)		2.687	0.948
HH-index SIC 2	Herfindahl-Hirschman index of industry turnover at 2-digit SIC code level	0.0509	0.0586
HH-index SIC 3	Herfindahl-Hirschman index of industry turnover at 3-digit SIC code level	0.0873	0.0938
HH-index SIC 4	Herfindahl-Hirschman index of industry turnover at 4-digit SIC code level	0.135	0.141
Market share SIC 2	Businesses' share in total industry turnover at 2-digit SIC code level	0.00264	0.0191
Market share SIC 3	Businesses' share in total industry turnover at 3-digit SIC code level	0.00806	0.0422
Market share SIC 4	Businesses' share in total industry turnover at 4-digit SIC code level	0.0177	0.0721
Employment	Employment matched from IDBR	217.3	1883.9
Log employment		3.099	2.089
Turnover		43485.4	632262
Turnover (logs)		7.471	2.479
GVA	Gross value added	14024.5	123541.1
GVA (logs)		6.684	2.331
R&D dummy	Conduct research and development work on a regular basis during the year	0.194	0.395
Foreign owned	Owned by a non-UK based organisation	0.0924	0.29
Agency employment	Share of agency employment in total employment cost	0.0243	0.663
Observations		429062	

Note: Sample corresponding to regression sample in table 3.4. Source: ARDX (ONS).

offering superior and unique products. On the other hand, innovation rents may be shared with employees (Van Reenen, 1996; Kline et al., 2019). A variable indicating the share of agency employment in total employment costs is a rough indicator for outsourcing of labour intensive tasks. Lastly, a dummy for foreign ownership is included.

3.4.Results

3.4.1 Descriptive analysis

Figure 3.1 shows different measures of industry concentration for Great Britain between 2002 and 2014 for different industry aggregations. Panel a) uses the Herfindahl-Hirschman index (HH-index). As industries defined by 4-digit SIC codes are the most narrowly defined, levels of concentration are overall higher than for 3-digit and 2-digit industries. At each level of aggregation, concentration has increased over the observation period. At the four-digit industry level, the HH-index increased from 0.14 in 2002 to 0.18 in 2014, with a peak of 0.2 in 2009, an increase of 30%. At the 3- and 2-digit industry levels, the index grew by 32% and 48%, respectively, over the period.

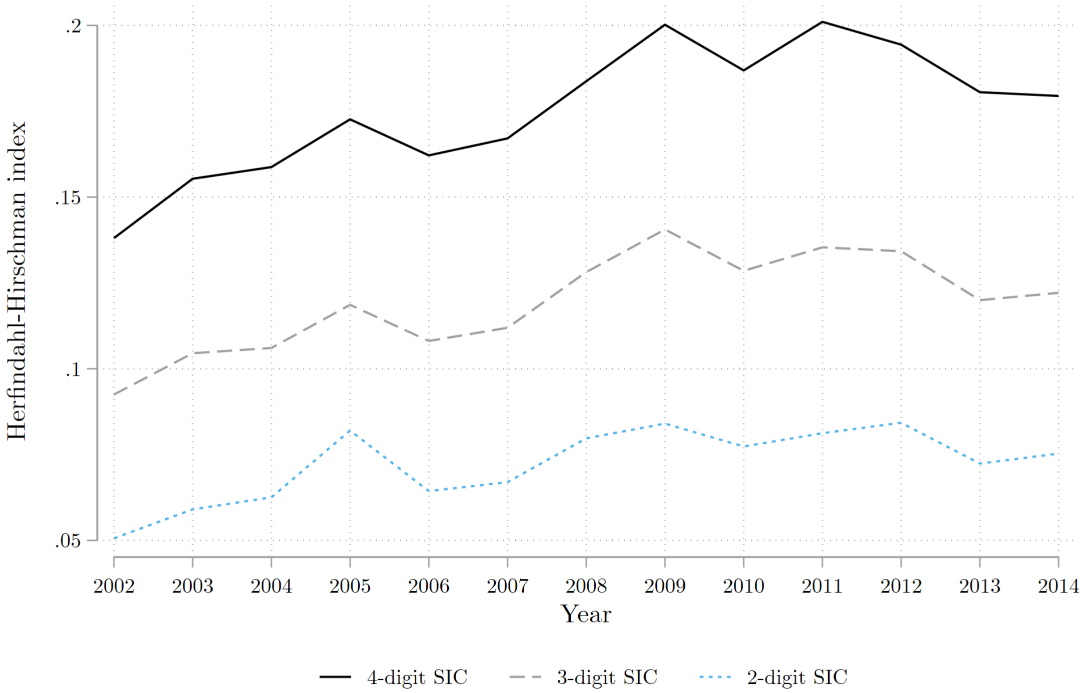
Panel b) of figure 3.1 considers concentration ratios as an alternative measure of industry concentration. While the HH-index takes into account the whole distribution of businesses within industries, the index number itself does not have a straightforward interpretation. Concentration ratios represent the share of the largest four (CR4) or largest twenty (CR20) businesses in total industry turnover. Panel b) in figure 3.1 shows that the largest four businesses in 4-digit industries accounted for 53% of industry turnover in 2002. This share increased to 62% in 2014, or by 17%. At the 3- and 2-digit industry levels, the turnover share by the largest four businesses grew by 21% and 36%, respectively, over the period.

Figure 3.1 considers industry concentration at the national level. This does not necessarily imply that industries are also spatially concentrated. In particular, Rossi-Hansberg, Sarte, and Trachter (2018) find that increasing concentration at the national level is associated with falling concentration at the local level, if dominant businesses open more local establishments. On the other hand, an industry that is not very concentrated can be spatially concentrated if all firms are located in a single cluster.

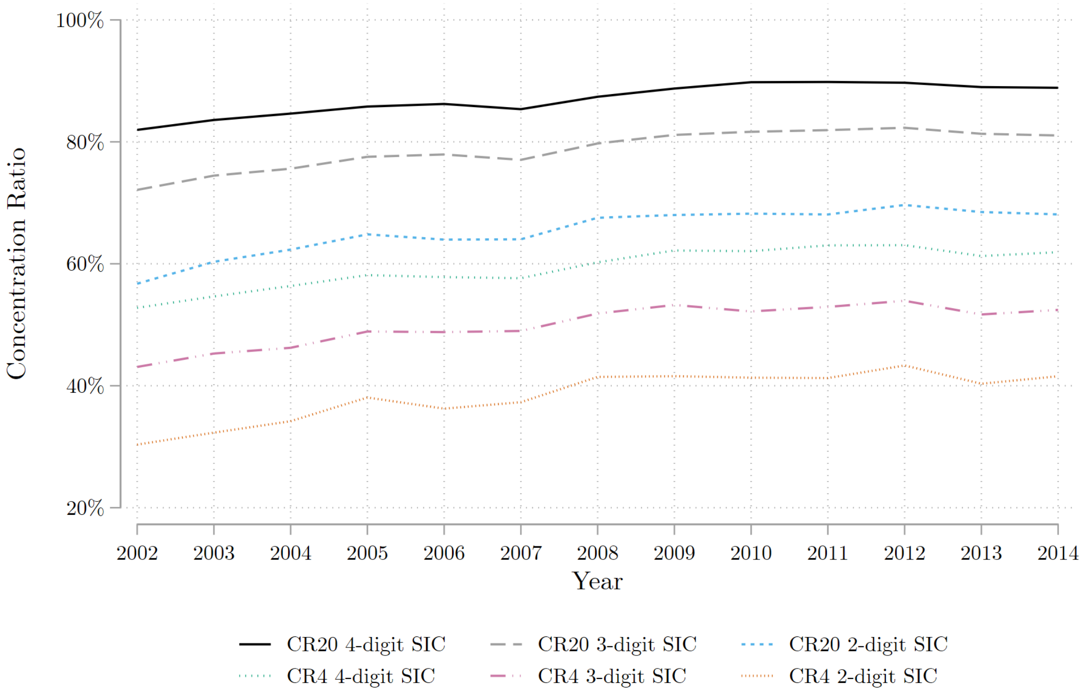
While it is not clear a priori whether concentrated industries are also geographically clustered, this is the case in the UK over the time period studied. Table 3.1 shows the correlation between national and regional concentration of an industry. As above,

Figure 3.1: Measures of industry concentration

a) Average Herfindahl-Hirschman index



b) Average concentration ratio



Note: Herfindahl-Hirschman index is measured as the sum of squared market shares at the industry level. CR4 and CR20 are the concentration ratios, or market shares of the largest 4 and largest 20 businesses by turnover. Industries are defined by 2-, 3-, or 4-digit SIC codes. All indices are first calculated at the industry level, and the average is weighted by total industry turnover. Source: ARDX (ONS), author's calculations.

national concentration is measured by firms' share of total industry turnover as the HH-index, CR4 and CR20. Regional concentration is measured as the HH-index of industry employment and value added across regions. For robustness, three different aggregations across NUTS1, 2 and 3 regions are presented. The top panel presents the correlation in levels, where observations are industry-years, while the bottom panel presents correlations in changes across the time period. Both in levels and differences, the correlations are positive and highly statistically significant. This shows that as industry concentration increases, industries tend to also become more regionally concentrated.

Table 3.1: Correlation between industry concentration and regional concentration

	Regional concentration					
Regions	NUTS1		NUTS2		NUTS3	
Metric	GVA	Emp	GVA	Emp	GVA	Emp
HH-index	0.716***	0.686***	0.762***	0.722***	0.782***	0.736***
CR4	0.578***	0.552***	0.606***	0.566***	0.613***	0.569***
CR20	0.330***	0.316***	0.345***	0.320***	0.346***	0.317***
N	7159	7159	7159	7159	7159	7159
	Change in regional concentration					
Regions	NUTS1		NUTS2		NUTS3	
Metric	GVA	Emp	GVA	Emp	GVA	Emp
Δ HH-index	0.580***	0.533***	0.620***	0.571***	0.633***	0.598***
Δ CR4	0.346***	0.315***	0.365***	0.328***	0.382***	0.349***
Δ CR20	0.166***	0.151***	0.171***	0.150***	0.183***	0.161***
N	525	525	525	525	525	525

* p <0.1, ** p <0.05, *** p <0.01.

Note: Correlation between regional concentration of GVA and employment with different measures of national industry concentration across firms by GVA. Regional units for the regional measure of concentration are indicated in the top line of the table. Unit of observation are industry-year averages defined by 4-digit SIC codes.

Given that industries are becoming more concentrated, and that concentrated industries tend to be more clustered, it is important to understand where dominant businesses are located. Table 3.2 provides a rough overview by counting the number of top-4 and top-20 businesses – measured by turnover, like the concentration ratios – for each NUTS1 region for different industry aggregations. This is only a rough measure as even the largest businesses in an industry with overall low levels of concentration do not have a lot of market power. Nonetheless, this concept aligns closely with the concentration ratios presented above, which are highly correlated with the Herfindahl-Hirschman indices. Table 3.2 shows that most dominant businesses can be found in London and the South East, the two richest regions by average incomes. The smallest numbers, by a large margin, can be found in Wales and the North East, two relatively poor regions. Regardless of the industry definition and whether the largest four or largest twenty businesses are considered to be dominant, the ranking of regions remains relatively stable. Naturally, some of these differences are driven by the total number of businesses in the regions, which are provided on the right-hand side of the table. However, it should be noted that these are unweighted counts, meaning that large businesses are overrepresented in the overall count, due to the sampling structure.

Table 3.2: Number of dominant businesses by NUTS1 region

Industry def.	4-digit SIC		3-digit SIC		2-digit SIC		Number of
Dominance def.	Top 4	Top 20	Top 4	Top 20	Top 4	Top 20	businesses
London	347	1321	175	744	71	330	4845
South East	271	1158	128	592	44	231	4688
North West	230	903	99	432	36	162	3184
Yorks & Humber	211	750	88	390	23	116	2509
West Midlands	209	812	87	435	24	131	2726
East of England	196	815	92	403	26	136	3194
Scotland	188	814	94	401	33	171	3894
East Midlands	163	668	69	321	22	107	2287
South West	156	664	70	345	<20	110	2714
Wales	77	310	36	172	<20	54	1155
North East	70	252	34	130	<20	48	902

Note: Number of businesses that are among the largest 4 or largest 20 by turnover in their industry, defined by 4-, 3- or 2-digit industries, in 2014. Reporting units with local units in multiple regions are allocated proportionally to local employment. All numbers are unweighted and are therefore not necessarily representative.

Table 3.3 relates industry concentration to industry average earnings, productivity and labour shares. Results are presented at the 2, 3 and 4 digit industry level as well as using the Hirschman-Herfindahl index and concentration ratios, to ensure results are not driven by the choice of indicator or industry aggregation. The underlying observations are industry-year averages. Throughout, there is a significant positive correlation between average earnings and labour productivity, measured as GVA per worker. As expected, the correlation with the labour share is negative. The next section will test these correlations in more detail.

Table 3.3: Correlation between industry concentration and earnings, productivity and labour shares

	HH-index	CR4	CR20
Average earnings	0.12***	0.10***	0.070***
GVA per worker	0.12***	0.12***	0.075***
Labour share	-0.062***	-0.13***	-0.12***
Number of underlying businesses	396708	396708	396708
Number of industries x years	7162	7162	7162

* p <0.1, ** p <0.05, *** p <0.01.

Note: Correlation between industry concentration measured by the Herfindahl index and concentration ratios (top-4 and top-20 share in turnover at the 4-digit industry level). Observations are industry-year averages. Industry definitions as indicated in the top row. Firms in top and bottom 0.1% of earnings, productivity and labour shares omitted.

3.4.2 Firm-level effects

This section presents estimation results of the effect of market power and industry concentration at the firm level. Table 3.4 presents estimates of the effect of industry concentration and market power on average wages and labour shares. All models define industries at the 4-digit SIC code level. Alternative specifications are explored in the appendix.

In the first, most simple model, only the Herfindahl-Hirschman index and the firm's share in total industry output, as well as industry and year fixed effects are included. The coefficient on the HH-index is negative and statistically significant, suggesting that firms in more concentrated industries have monopsony power and are able to set lower wages. However, the coefficient on a firm's individual market share is positive. This has two possible explanations. More productive firms may be able to capture a larger market share, with higher labour productivity reflected in higher wages. Alternatively, rents captured due to market power may be passed on to workers in the form of higher wages.

In the second specification, further firm-level controls are added, including log employment, dummies indicating whether the firm conducts R&D or is foreign-owned, and the share of agency employment in total employment costs. The coefficient on the HH-index becomes statistically insignificant, while the coefficient on the market share falls in magnitude but remains statistically significant.

In the third specification, the interaction of the two variables of interest is included, as the market power a firm can exercise also depends on the overall level of concentration of the industry. The coefficient of the HH-index remains statistically insignificant, while that of the market share doubles in magnitude. The coefficient of the interaction is statistically significant and negative. Overall, the marginal effect of the market share remains positive, while that of the HH-index remains statistically insignificant, as shown at the bottom of the table. If a firms market share increased by one percentage point, average annual wages would be expected to increase by about £1,012. At the average annual wage of £33,640, this is a quite substantial increase of 3%. Figure 3.2 plots the marginal effect of the market share against different levels of the HH-index. The figure shows a larger effect of market share for lower levels of industry concentration. This points to the importance of the overall competitive environment, not just the individual market share. For example, in an industry that is otherwise characterised by a large number of small firms, a firm that is larger than most others by some margin may have some market power despite not possessing a large overall market share. On the other side of the spectrum, highly concentrated markets may be highly competitive, so that even firms with large market shares have relatively little market power. An example of this are supermarkets in the UK. However, there is no guarantee that a concentrated market turns into a competitive oligopoly, as Philippon (2019) demonstrates with the example of the telecoms and airlines markets.

The control variables included have the expected effects. Average wages are higher at larger firms as measured by log employment. Firms that undertake R&D or are foreign owned also pay higher wages. In contrast, wages are lower at firms that use more agency workers, a practice that is more common in low-paid industries.

The next set of results shows estimations for the labour share as the dependent variable. When only the HH-index and market share are included as explanatory variables, neither has a statistically significant effect. When more control variables are included, the effect of the HH-index becomes positive and statistically significant, while that of the market share

Table 3.4: Regression of wages and labour shares on market power and concentration

Dep. Var.:	Average wage (logs)			Labour share		
	(1)	(2)	(3)	(4)	(5)	(6)
Market share	2.16***	0.55***	1.15***	0.0099	-0.49***	-1.07***
	(0.076)	(0.10)	(0.22)	(0.016)	(0.025)	(0.047)
HH-index	-0.22***	-0.045	0.023	-0.014	0.042***	-0.023**
	(0.038)	(0.029)	(0.028)	(0.012)	(0.0095)	(0.010)
HH-index x mkt sh			-1.12***			1.08***
			(0.24)			(0.058)
Log employment		0.14***	0.14***		0.055***	0.058***
		(0.0096)	(0.010)		(0.0018)	(0.0018)
R&D dummy		0.033***	0.032***		-0.0014	-0.00069
		(0.010)	(0.010)		(0.0022)	(0.0021)
Foreign owned		0.27***	0.27***		-0.052***	-0.046***
		(0.022)	(0.022)		(0.0043)	(0.0042)
Agency emp. share		-0.020**	-0.020**		-0.0062**	-0.0061**
		(0.0091)	(0.0092)		(0.0026)	(0.0026)
Constant	2.68***	2.22***	2.21***	0.56***	0.39***	0.39***
	(0.0052)	(0.030)	(0.029)	(0.0015)	(0.0057)	(0.0056)
R2	0.15	0.23	0.24	0.12	0.25	0.26
adj. R2	0.15	0.23	0.23	0.12	0.25	0.26
N	429057	429057	429057	429057	429057	429057
dydx HH-index			0.023			-0.023
dydx market share			1.15			-1.07

* p <0.1, ** p <0.05, *** p <0.01.

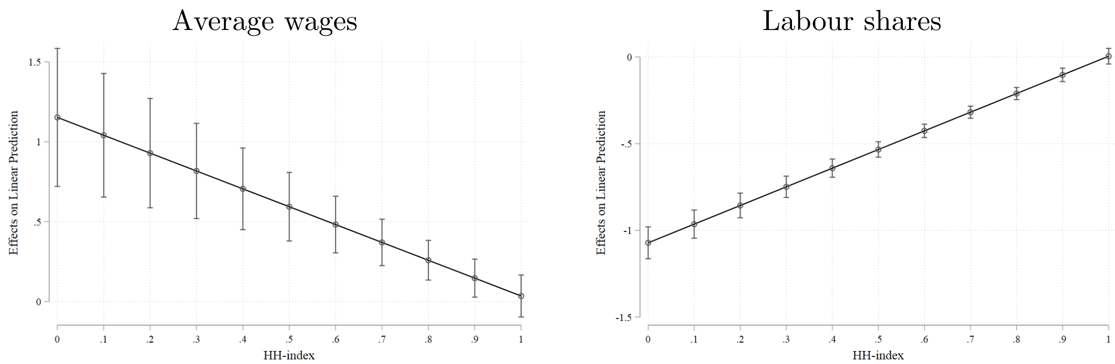
Note: Market share and Herfindahl-Hirschman (HH-) index defined at the 4-digit SIC code level. All specifications including year and 4-digit SIC code industry fixed effects. dydx indicates the marginal effect of changes in the variable, taking into account the interaction effect. Robust standard errors clustered at the industry level provided in parentheses.

becomes negative. As expected, these effects are the opposite of the effects for average wages. This suggests that firms with market power are able to capture rents that are not fully shared with workers, so that the share of wages in GVA declines.

When the interaction is included, the negative coefficient on the market share increases in magnitude and the coefficient on the HH-index flips to negative. The coefficient on the interaction is positive, but the marginal effects on both variables remain negative, as indicated at the bottom of the table. Figure 3.2 shows the marginal effect of the market share on the labour share for different levels of industry concentration. As with the effect on wages, the graph shows the largest, in this case negative, effect for lower levels of industry concentration.

In terms of the control variables, the labour share is higher at larger firms. There is no effect from R&D, which demonstrates again that, while innovation rents may be shared with workers (Van Reenen, 1996), this does not necessarily affect the labour share. The labour share is lower in foreign owned firms, which may be a result of lower bargaining power of employees at multinational enterprises. Unsurprisingly, the labour share is larger in firms that use agency employment, as some of the labour is outsourced.

Figure 3.2: Marginal effect of market power on average earnings and labour shares



Note: The figures show the marginal effects of market share on average wages and labour shares, respectively, for different levels of industry concentration. The figure is derived from specifications 3 and 6 in table 3.4.

The appendix presents some robustness checks for these results. Table 3.D.2 repeats specification three and six with market share and industry concentration measured at the 2-digit and 3-digit SIC code level. While the coefficients change in magnitude, their sign remains unchanged. Table 3.D.4 utilises the panel aspect of the survey and only includes businesses with at least two survey responses available. Summary statistics for the restricted sample are provided in table 3.D.3, showing that these businesses are on average larger and pay higher wages than the full sample. Because the sample is less representative of the British economy as a whole, it is not used for the main results. The regression controls for business fixed effects, therefore controlling for any unobserved characteristics of the business. For average wages, the results are slightly different, with a significant negative coefficient of the HH-index instead of a positive insignificant one, and a negative effect of log employment. The marginal effect of the the HH-index flips negative, but remains small in magnitude compared to the effect of market power. The coefficients in the labour share regressions have the same sign as in the full sample regressions.

3.4.3 Regional impacts

Businesses with market power may have big impacts on local labour markets. As industries are dominated by fewer, larger firms, employment is more concentrated, and, as table 3.1 shows, industries that are more concentrated are also more spatially concentrated. Concentration increases if existing businesses cease trading and are not replaced by new entrants. Given the constant churn in the economy, it is impossible to say where businesses would have been located had they entered the market or not left the market in the first place. However, based on the regression analysis above, it is possible to calculate the contribution of concentration on average wages and labour shares at the regional level.

Table 3.5 provides a calculation of the regional distribution of the effect of market power and industry concentration on average wages. The effect is calculated from the regression coefficients in table 3.4, multiplied by market power and industry concentration at the firm level and averaged at the regional level. The averages are weighted by survey design weights[2] as well as log employment, to give more weight to larger businesses. Reporting units, which are collections of local units such as plants, offices and branches for which financial information is available, are allocated to regions based on local employment. The weights required to create aggregates from the survey sample are only available from 2003, so the 2003-2014 horizon is used for the calculation.

[2]The weights consist of sampling weights that are based on the sampling frame and reflect the lower probability of smaller businesses to be sampled, as well as the differences in sampling across industries. Additionally, calibration weights are used to adjust for unusual values in the sample using additional data. These adjustments are used to account for sampling variation and to achieve greater stability in the data. The calibration weights used here are based on turnover. For details on the weight design see https://www.ons.gov.uk/businessindustryandtrade/business/businessservices/methodologies/annualbusinesssurveytechnicalreportaugust2018

The first two columns in table 3.5 show log wages (in thousands) and the effect of market power and concentration on wages in 2003 by region. The contribution of market power and industry concentration to wage growth is calculated as the change in the effect divided by the change in wages. However, the effects are overall quite small. The contributions are negative for London and the South East, the two regions with the highest earnings, but for opposing reasons: in London, wages were stagnant, but the average market share of businesses actually declined, with this negative impact counteracted by other forces. In the South East, on the other hand, wages fell, but by less than otherwise expected, because of an increase in market power of local firms. At the bottom of the table, decline in market power of local firms contributed to falling average wages in the North East.

Table 3.5: Effect of market power and industry concentration on average wages by NUTS1 region, 2003-2014

NUTS1 region	2003 wages (log) [1]	2003 Effect of market power & concentration on wages [2]	2014 wages (log) [3]	2014 Effect of market power & concentration on wages [4]	Wage growth attributable to market power & concentration ([4]-[2])/([3]-[1])
London	2.60	0.0076	2.60	0.0067	-96.10%
South East	2.44	0.0067	2.43	0.0070	-4.02%
West Midlands	2.40	0.0074	2.41	0.0071	-2.48%
East Midlands	2.40	0.0066	2.33	0.0070	-0.54%
North West	2.34	0.0069	2.30	0.0070	-0.20%
Wales	2.36	0.0063	2.23	0.0064	-0.08%
Yorks. & Humber	2.40	0.0072	2.28	0.0073	-0.08%
Scotland	2.53	0.0079	2.39	0.0073	0.43%
South West	2.31	0.0066	2.29	0.0062	1.77%
East of England	2.38	0.0061	2.40	0.0067	2.15%
North East	2.36	0.0077	2.35	0.0070	13.01%

Note: Effect of market power and industry concentration on average wages based on specification 3 in table 3.4. Observations are weighted by survey designed weights (a-weight and g-weight) and log employment.

As a result of the global financial crisis in 2008 and 2009, wage growth over the period was overall very low. Figure 3.C.1 in the appendix shows the trends in average wages over the whole period, with the negative effect of the financial crisis clearly visible in 2008 and 2009. After 2009, wages remained largely stable, albeit, in many regions at a lower level. It should be noted that these are average wages per employee: the reduction in average wages may be the result of reduced hourly rates, reduced hours, or a shift in the composition of employment to lower-paid roles. Table 3.D.5 in the appendix replicates the analysis for two sub-periods, 2003 to 2007 and 2010 to 2014, that were less affected by the recession. In the first period, growing concentration uniformly contributed to growing wages. In the second period, concentration offset some of the decline in average wages, such as in Scotland, the South East, Wales and Yorkshire and the Humber.

Table 3.6 repeats the analysis for the effect on labour shares. In all regions, labour shares fell between 2003 and 2014. By 2014, labour shares were lowest in London and the South East, the two highest paying regions, albeit with a small margin. Similar to the effect on wages, the overall contribution of market power and concentration is small, up to 2% of total change in labour shares. Again, the analysis is repeated for the two periods before and after the financial crisis in table 3.D.6 in the appendix. This shows that the labour share increased in some regions in the first half of the observation period, but uniformly fell in the second. Between 2010 and 2014, increasing industry concentration contributed to the decline in the labour share in most regions. In the South East, it contributed almost 6% of the decline in the labour share. While London experienced a steep decline in the labour share between 2010 and 2014, growing concentration did not contribute to this trend.

Table 3.6: Effect of market power and industry concentration on labour shares by NUTS1 region, 2003-2014

NUTS1 region	2003 labour share [1]	2003 Effect of market power & concentration on LS [2]	2014 labour share [3]	2014 Effect of market power & concentration on LS [4]	LS change attributable to market power & concentration ([4]-[2])/([3]-[1])
North East	55.9%	-0.0073	53.1%	-0.0067	-2.04%
London	56.0%	-0.0072	49.9%	-0.0064	-1.33%
Scotland	57.9%	-0.0075	52.1%	-0.0070	-0.81%
South West	56.5%	-0.0063	50.9%	-0.0060	-0.53%
West Midlands	56.3%	-0.0070	50.7%	-0.0068	-0.32%
Wales	60.3%	-0.0059	51.7%	-0.0062	0.30%
North West	55.8%	-0.0066	51.4%	-0.0067	0.34%
Yorks & Humber	55.8%	-0.0068	51.3%	-0.0070	0.40%
East Midlands	56.6%	-0.0063	51.6%	-0.0067	0.81%
South East	54.7%	-0.0063	50.4%	-0.0067	0.88%
East of England	53.1%	-0.0058	50.2%	-0.0064	2.09%

Note: Effect of market power and industry concentration on average wages based on specification 6 in table 3.4. LS indicates labour share. Observations are weighted by survey designed weights (a-weight and g-weight) and log employment.

3.5.Discussion and conclusion

The analysis shows strong impacts of market power on wages and labour shares at the firm level in the UK. Market concentration has grown significantly in recent years. The evidence suggests that this gives firms market power and the ability to charge mark-ups over marginal cost. While these rents are partially shared with workers, labour shares fall, with possibly negative effects on overall interpersonal inequality. Concentrated industries also become more regionally clustered, however, the overall effects at the regional level are small. While these results add to the international evidence on the growing importance of dominant firms, future research needs to consider the underlying mechanisms driving these effects.

At the firm level, market power is associated with higher wages. This may be a signal of higher productivity: more productive firms may be able to capture a higher market share and also pay higher wages. However, this does not square with the negative effect of market power on labour shares. If gains in productivity were shared with workers, productivity increases would translate into higher wages and a constant labour share. In the model proposed by Autor et al. (2020), higher productivity is manifested in a smaller share of overhead labour, which also results in a lower labour share. But it is not clear what their model predicts for average wages. In contrast, efficiency wage models (Akerlof & Yellen, 1990; Blanchflower et al., 1996) can explain both the effect on wages as well as on labour shares, if profits are only partially shared with workers.

One aspect that could not be explored with the available data is the effect on regional earnings through business dynamics, as only wages and labour shares at surviving businesses are observed. Businesses with high market shares may be able to achieve their dominance by forcing competitors out of business. Feldman et al. (2021) show how large businesses may negatively affect growth in left-behind regions in the United States through acquisitions of promising start-ups, thereby depriving those regions of growth prospects. The effects of industry concentration may therefore be wider, if business growth in regions outside of established clusters is stifled. The co-location of dominant firms and very small firms could be directly related, as highly productive firms tend to outsource more and more functions to smaller firms or self-employed sub-contractors (Card et al., 2013; Weil, 2014). In the UK context, this is facilitated by liberal labour market institutions that have fuelled the growth of self-employment and other forms of non-standard working such as through employment agencies and umbrella companies in recent years (Green & Livanos, 2015).

This makes it important to understand the wider compositional changes. Concentration can increase if the overall number of businesses declines, or if market shares become more unequally distributed between smaller and larger businesses. A widening gap between a small number of market leaders and a long tail of possible challengers that find it difficult to gain scale may also contribute to widening inequalities within regions, an aspect not considered in this chapter.

This links to the factors that allow firms to achieve dominance in the first place. Research shows that regional characteristics can contribute to a firm's growth to industry dominance through external economies of scale, such as supplier networks, deep labour pools and knowledge exchange (Duranton & Puga, 2004). If industries are becoming more and more concentrated, the only chance for a start-up to "make it" may then be by locating in a highly productive city (Gaubert, 2018), further deepening inequalities. The interaction between agglomeration effects and market power may then make it very difficult for lagging regions to attract new firms and industries (Feldman et al., 2019).

To better understand the mechanisms at play, future research needs to unpack the mechanisms by which industries become more concentrated. Some firms gain market power through strategic acquisitions (Argentesi et al., 2020; Cunningham, Ederer, & Ma, 2021). Others may grow organically to dominate a market, or disrupt an industry through innovation. The dynamics are highly specific to individual industries. Some industries, in particular traditional manufacturing and service industries have low barriers to entry, but incumbents may fend of competition through acquisitions or predatory pricing, whereby the incumbent takes temporary losses to undercut a challengers prices and drive them out of business. In contrast, many digital industries, but also those requiring high upfront tangible or intangible investments and technologies exhibiting network effects, may be natural monopolies.

The present study cannot establish causality between market power, industry concentration, wages and labour shares. Although the combination of positive effects on wages and negative effects on labour shares presents some compelling evidence in favour of a rent sharing model, future research will uncover the specific components of this model. Estimating rents is difficult as firms' marginal costs are unobserved, but it is possible to do so (De Loecker & Eeckhout, 2018). This could provide more evidence on the relation between market power, rents and wages, and labour shares. Combined with more evidence on the structure of the market, as outlined above, this could also uncover the source of rents. Some market power is legitimate, for example, market power conferred by patent protection, which allows inventors to earn rents to recover the costs of the invention (Kline et al., 2019). In other cases, this may come at the detriment of consumers, through higher prices. Here, price comparisons across countries can provide insights (Gutiérrez & Philippon, 2019). This measure is not useful in many digital markets, where the products are free to consumers, or platforms, that help consumers to find lower prices. Instead, in these markets high rents are achieved by exercising monopsony power over suppliers of inputs.

If the rent-sharing model hypothesised here is accurate, the question remains over how the share of the rents earned by workers is determined. Stansbury and Summers (2020) argue that worker power has declined in particular as a result of falling unionisation. Many workers have strong preferences for low inequality within a work place, resulting in higher wages for those with otherwise low bargaining power (Akerlof & Yellen, 1990). However, recent increases in outsourcing and the use of non-standard employment contracts have weakened bargaining power (Weil, 2014), or what Stansbury and Summers (2020) call "ruthless" management practices, as opposed to the fair wage model by Akerlof and Yellen

(1990). On the other hand, there is evidence that public pressure, in particular on large employers can result in higher pay, even outside the targeted firms (Derenoncourt et al., 2021).

Appendix

3.A.Mark-up model

Consider the following Cobb-Douglas production function:

$$Y = AL^{\alpha}K^{1-\alpha}$$

Under perfect competition, workers are paid their marginal product, $\delta Y/\delta L$:

$$\delta Y/\delta L = \alpha A(\frac{K}{L})^{1-\alpha} = w$$

Then, the labour share can be written as:

$$LS = \frac{wL}{Y} = \frac{\alpha A(\frac{K}{L})^{1-\alpha}L}{AL^{\alpha}K^{1-\alpha}} = \alpha$$

If firms are able to charge a mark-up m over cost, total nominal output is $Y + mY = (1+m)Y$. If workers are able to capture share s of the mark-up, the new labour share can be written as:

$$\tilde{LS} = \frac{smY + wL}{(1+m)Y}$$

Let us consider under which conditions the labour share remains constant, so that $LS = \tilde{LS}$:

$$
\begin{aligned}
\frac{wL}{Y} &= \frac{smY + wL}{mY + Y} \\
wLmY + wLY &= smY^2 + wLY \\
wLm &= smY \\
wL &= sY \\
s &= \frac{wL}{Y} = \alpha
\end{aligned}
$$

Therefore, if $m > 0$, the labour share will remain constant only if $s = \alpha$, increase if $s > alpha$, and decrease if $s < alpha$.

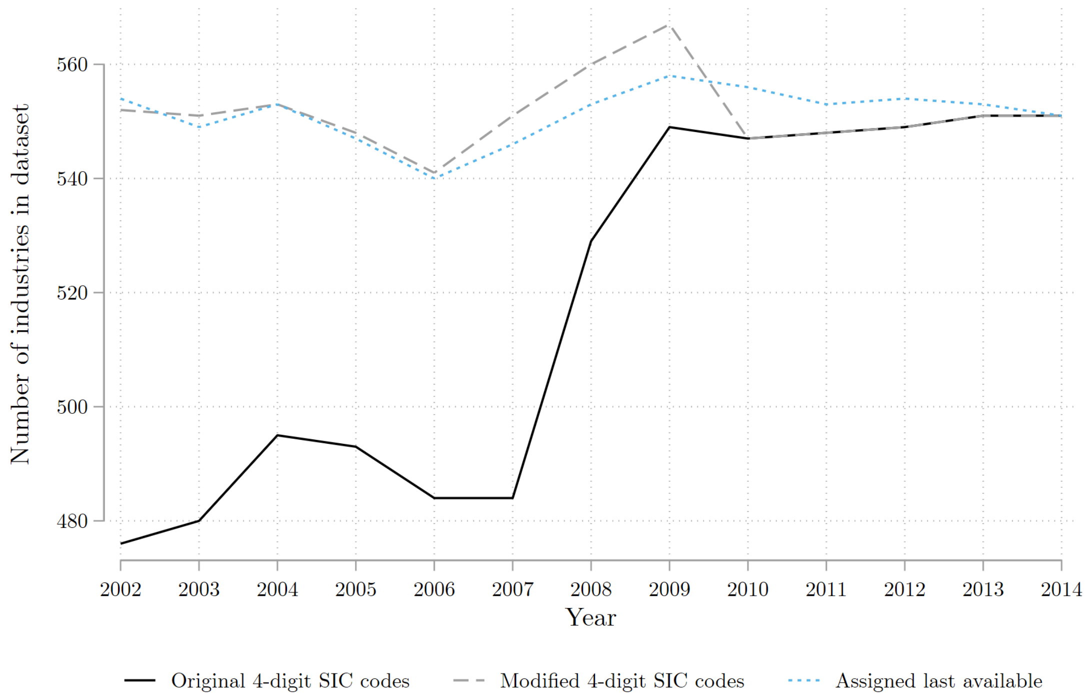
3.B.Harmonising 2003 and 2007 SIC codes

Industrial classifications change to reflect changes in the structure of the economy. UK SIC codes changed in 2003 and 2007. As the ARDX is designed as a panel dataset, researchers have imputed 2007 SIC codes for the 1998 to 2007 period. However, an unusually large number of businesses changed SIC code in 2003, 2008 and 2009, implying that measures of industry concentration may be distorted. Moreover, the number of industries in the dataset increases over time. This may result in a measured increase in industry concentration because the same number of businesses are spread over a rising number of industries. To mitigate these factors, I adjusted SIC codes to reduce volatility in SIC codes and to hold the number of industries in the dataset roughly stable over time. One simple solution might be to use the last available SIC code for every business throughout its history. However, businesses may reasonably change their main activity over time. I therefore adjusted SIC codes with a view to eliminate the spike in reassignments in 2003 and 2008/2009 according to the following rules:

1. For years after 2009, make no adjustments and use the available SIC code.
2. If a firm never changes SIC code, use the assigned SIC code.
3. If a firm changed SIC code once, use the assigned SIC code, unless the change occurred in 2003, 2008 or 2009.
4. In all other cases, use the last available SIC code.

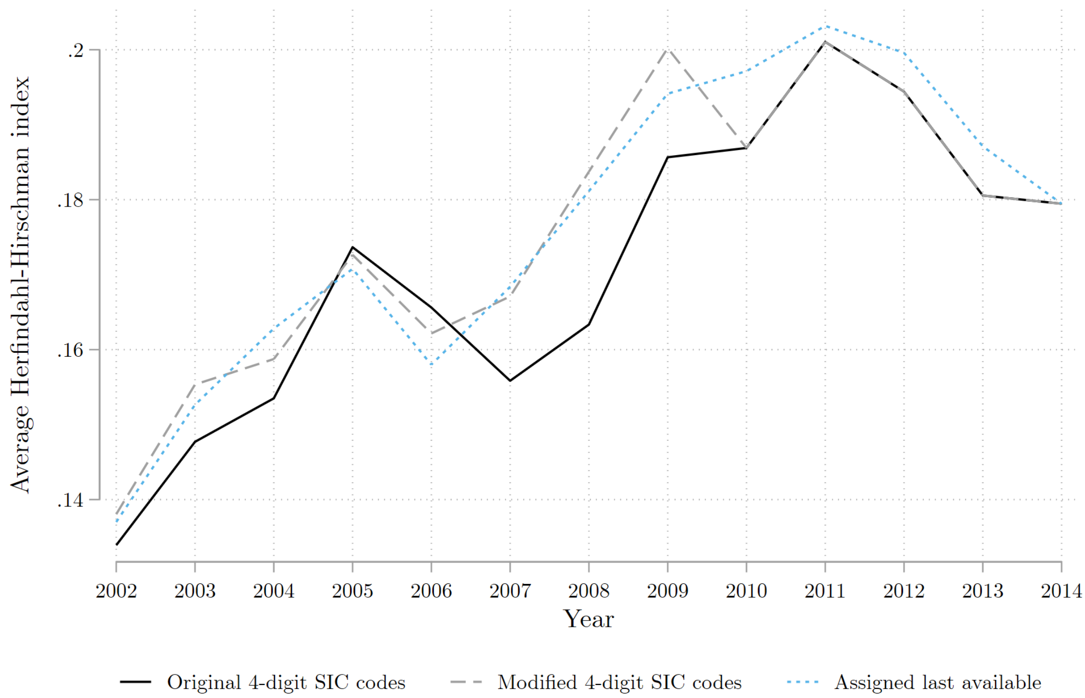
As most firms are not captured by the ARDX each year, the SIC code assignment is done using universe files, where all firms in the ARDX sampling frame are included each year, with SIC codes drawn from the Figure 3.B.1 shows the number of industries per year. Figure 3.B.2 replicates figure 3.1 but showing Hirschman-Herfindahl indices at the 4-digit SIC code level using original SIC codes, assigning the last available SIC code, and the modified SIC codes as explained above, which are used throughout the main analysis.

Figure 3.B.1: Number of industries in the dataset using alternative modifications



Note: All SIC codes are according to the 2007 classification, but the number of industries varies depending on the method to update older SIC codes for the years before 2008. Original SIC codes as in ARDX, modified SIC codes as described in the text, and last available assigning the last available code for each business.

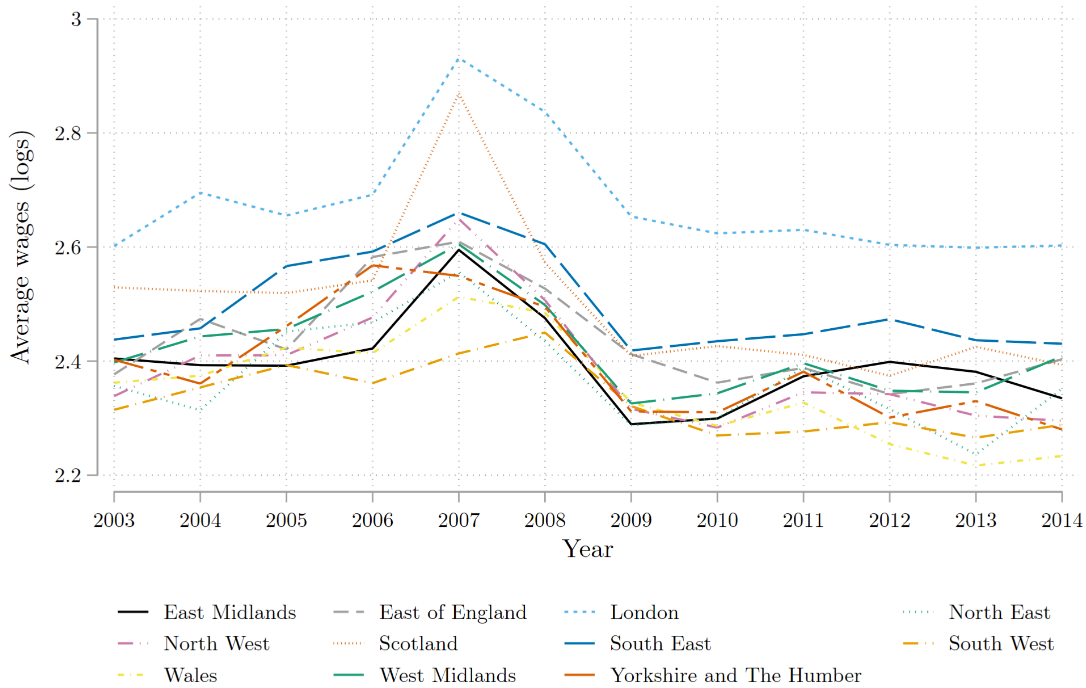
Figure 3.B.2: Average Herfindahl-Hirschman index for alternative industry definitions



Note: Average Herfindahl-Hirschman index for 4-digit industries with different modifications to update older SIC codes for the years before 2008. Original SIC codes as in ARDX, modified SIC codes as described in the text, and last available assigning the last available code for each business.

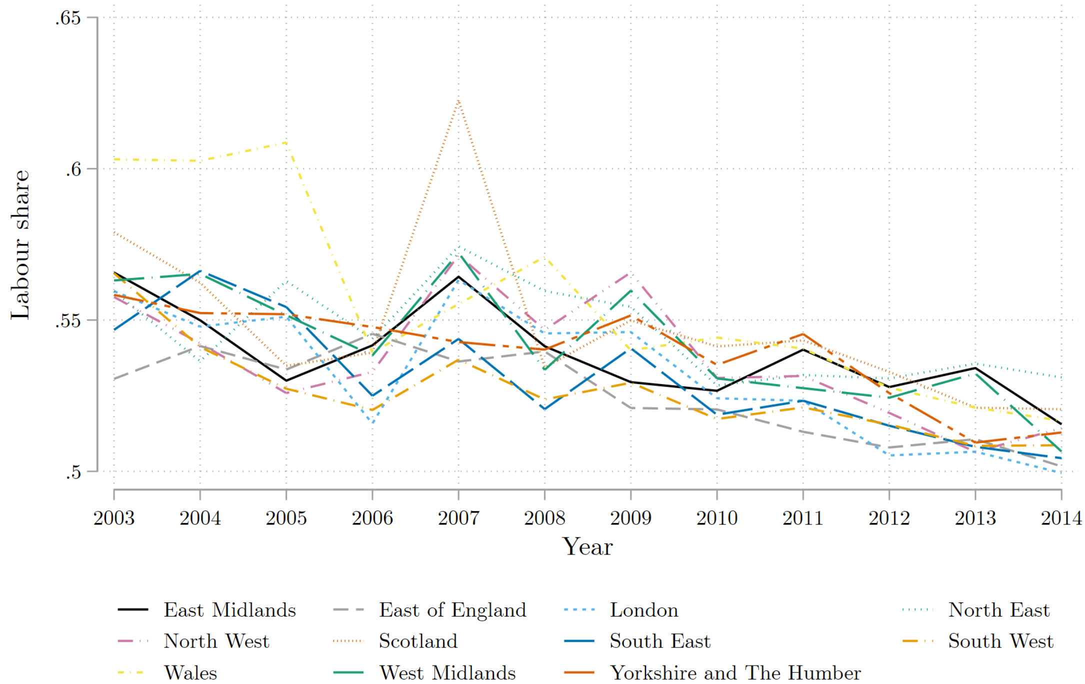
3.C. Additional figures

Figure 3.C.1: Average wages by NUTS1 region



Note: Average wages calculated as weighted average from reporting unit level wages, weighted by a-weight x g-weight x log employment. Reporting units with local units in multiple regions are allocated based on local unit employment shares. Source: ARDX (ONS), author's calculations.

Figure 3.C.2: Labour share by NUTS1 region



Note: Regional labour share calculated as weighted average from reporting unit level labour shares, weighted by a-weight x g-weight x log employment. Reporting units with local units in multiple regions are allocated based on local unit employment shares. Source: ARDX (ONS), author's calculations.

3.D.Additional tables

Table 3.D.1: Correlation between industry concentration and earnings, productivity and labour shares – alternative industry aggregations

	2-digit SIC			3-digit SIC		
	HH-index	CR4	CR20	HH-index	CR4	CR20
Average earnings	0.096***	0.21***	0.27***	0.16***	0.17***	0.13***
GVA per worker	0.20***	0.25***	0.27***	0.18***	0.16***	0.11***
Labour share	-0.16***	-0.33***	-0.37***	-0.11***	-0.18***	-0.16***
N businesses	396708	396708	396708	396708	396708	396708
N industries x years	1082	1082	1082	3271	3271	3271

* p <0.1, ** p <0.05, *** p <0.01.

Note: Correlation between industry concentration measured by the Herfindahl index and concentration ratios (top-4 and top-20 share in turnover at the 4-digit industry level). Observations are industry-year averages. Industry definitions as indicated in the top row. Firms in top and bottom 0.1% of earnings, productivity and labour shares omitted.

Table 3.D.2: Regression results for alternative industry aggregations

Dep. Var.:	Average wage (logs)		Labour share	
Industry aggregation:	SIC 2	SIC 3	SIC 2	SIC 3
Market share	1.60**	1.22***	-2.85***	-1.54***
	(0.72)	(0.35)	(0.23)	(0.087)
HH-index	0.094	0.022	0.014	-0.023
	(0.098)	(0.047)	(0.025)	(0.014)
HH-index x mkt sh	-1.88**	-1.32***	3.44***	1.68***
	(0.92)	(0.41)	(0.40)	(0.12)
Log employment	0.14***	0.14***	0.055***	0.056***
	(0.012)	(0.011)	(0.0028)	(0.0021)
R&D dummy	0.041***	0.038***	-0.0030	-0.0014
	(0.015)	(0.013)	(0.0032)	(0.0026)
Foreign owned	0.31***	0.29***	-0.061***	-0.053***
	(0.043)	(0.027)	(0.0058)	(0.0051)
Agency emp. share	-0.019**	-0.019**	-0.0063**	-0.0061**
	(0.0088)	(0.0090)	(0.0027)	(0.0026)
Constant	2.21***	2.21***	0.39***	0.40***
	(0.036)	(0.033)	(0.0087)	(0.0067)
R2	0.21	0.22	0.24	0.25
adj. R2	0.21	0.22	0.24	0.25
N	429057	429057	429057	429057
dydx HH-index	0.094	0.022	0.014	-0.023
dydx market share	1.60	1.22	-2.85	-1.54

* p <0.1, ** p <0.05, *** p <0.01.

Note: Market share and Herfindahl-Hirschman (HH-) index defined at the SIC code level as indicated at the top of the table. All specifications including year and industry fixed effects at the same level of aggregation as concentration variables. dydx indicates the marginal effect of changes in the variable, taking into account the interaction effect. Robust standard errors clustered at the industry level provided in parentheses.

Table 3.D.3: Summary statistics for panel sample

	Mean	SD
Labour share	0.628	0.223
Average wage (th£)	40.92	394.2
Average wages/salaries (logs)	2.996	0.758
HH-index SIC 2	0.05	0.0587
HH-index SIC 3	0.0884	0.0952
HH-index SIC 4	0.137	0.142
Market share SIC 2	0.00467	0.025
Market share SIC 3	0.014	0.0544
Market share SIC 4	0.0303	0.0923
Employment	388	2545.4
Log employment	4.464	1.577
Turnover	78746.9	861658.7
Turnover (logs)	9.027	1.941
GVA	25253.5	165278.5
GVA (logs)	8.16	1.818
R&D dummy	0.219	0.414
Foreign owned	0.155	0.362
Agency emp. share	0.0294	0.746
Observations	227389	

Table 3.D.4: Regression results for panel sample

Dep. var.:	Average wage (logs)			Labour share		
Industry aggregation:	SIC 2	SIC 3	SIC 4	SIC 2	SIC 3	SIC 4
Market share	2.87***	1.60***	1.16***	-0.58***	-0.35***	-0.23***
	(0.23)	(0.090)	(0.054)	(0.083)	(0.036)	(0.021)
HH-index	-0.078**	-0.050**	-0.028*	-0.0015	-0.0091	-0.0082
	(0.033)	(0.020)	(0.015)	(0.014)	(0.0089)	(0.0064)
HH-index x mkt sh	-3.12***	-1.63***	-1.03***	0.63***	0.36***	0.22***
	(0.29)	(0.13)	(0.061)	(0.12)	(0.049)	(0.026)
Log employment	-0.42***	-0.42***	-0.43***	0.028***	0.028***	0.029***
	(0.0065)	(0.0065)	(0.0065)	(0.0015)	(0.0015)	(0.0015)
R&D dummy	0.00025	0.0010	0.0010	0.0027**	0.0026**	0.0025**
	(0.0027)	(0.0026)	(0.0026)	(0.0013)	(0.0013)	(0.0013)
Foreign owned	-0.0039	-0.0037	-0.0032	-0.0014	-0.0012	-0.0015
	(0.0056)	(0.0056)	(0.0056)	(0.0025)	(0.0025)	(0.0025)
Agency emp. share	-0.017**	-0.017**	-0.017**	-0.0010	-0.0010	-0.0010
	(0.0067)	(0.0067)	(0.0067)	(0.00098)	(0.00098)	(0.00098)
Constant	4.87***	4.87***	4.88***	0.50***	0.51***	0.51***
	(0.029)	(0.029)	(0.029)	(0.0067)	(0.0067)	(0.0067)
R2	0.87	0.87	0.87	0.69	0.70	0.70
adj. R2	0.81	0.81	0.81	0.57	0.57	0.57
N	227389	227389	227389	227389	227389	227389
dydx HH-index	-0.078	-0.050	-0.028	-0.0015	-0.0091	-0.0082
dydx market share	2.87	1.60	1.16	-0.58	-0.35	-0.23

* p <0.1, ** p <0.05, *** p <0.01.

Note: Only includes reporting units (firms) occurring at least twice on ARDX. Market share and Herfindahl-Hirschman (HH-) index defined at the SIC code level as indicated at the top of the table. All specifications including reporting unit, year and industry fixed effects at the same level of aggregation as concentration variables. dydx indicates the marginal effect of changes in the variable, taking into account the interaction effect. Robust standard errors clustered at the industry level provided in parentheses.

Table 3.D.5: Effect of market power and industry concentration on regional wages for alternative time periods

	2003-2007		2010-2014		2003-2014	
NUTS1 region	Wage growth	Wage growth due to market power & concentration	Wage growth	Wage growth due to market power & concentration	Wage growth	Wage growth due to market power & concentration
East Midlands	19.04%	1.15%	3.54%	0.30%	-6.99%	-0.54%
East of England	23.27%	1.19%	4.11%	0.78%	2.65%	2.15%
London	32.97%	0.56%	-2.12%	0.86%	0.10%	-96.10%
North East	19.97%	2.11%	5.17%	-0.04%	-0.50%	13.01%
North West	31.08%	0.79%	1.20%	1.95%	-4.31%	-0.20%
Scotland	34.03%	1.04%	-3.28%	-1.01%	-13.57%	0.43%
South East	22.28%	0.35%	-0.43%	-20.31%	-0.72%	-4.02%
South West	9.87%	1.38%	1.86%	1.95%	-2.64%	1.77%
Wales	15.06%	2.57%	-5.26%	-0.10%	-12.85%	-0.08%
West Midlands	20.72%	0.90%	6.50%	-0.21%	1.09%	-2.48%
Yorks & Humber	14.70%	1.18%	-2.99%	-0.11%	-12.23%	-0.08%

Note: The table shows the share of wage growth that is attributable to changing market power and industry concentration. This is calculated as the effect of the change in market power and industry concentration, derived from specification 3 in table 3.4, divided by overall wage growth in the region. Observations are weighted by survey designed weights (a-weight and g-weight) and log employment.

Table 3.D.6: Effect of marker power and industry on regional labour shares for alternative time periods

	2003-2007		2010-2014		2003-2014	
NUTS1 region	Labour share change	LS change due to market power & concentration	Labour share change	LS change due to market power & concentration	Labour share change	LS change due to market power & concentration
East Midlands	-0.14	136.39%	-1.11	0.78%	-5.01	0.81%
East of England	0.57	-45.07%	-1.88	1.67%	-2.89	2.09%
London	0.37	-46.41%	-2.47	-0.64%	-6.01	-1.33%
North East	1.49	-26.36%	0.27	0.94%	-2.84	-2.04%
North West	1.38	-16.19%	-1.66	1.43%	-4.33	0.34%
Scotland	4.37	-7.39%	-2.07	1.43%	-5.85	-0.81%
South East	-0.30	25.03%	-1.44	5.87%	-4.24	0.88%
South West	-2.86	4.38%	-0.87	4.15%	-5.68	-0.53%
Wales	-4.78	7.68%	-2.75	0.30%	-8.64	0.30%
West Midlands	0.92	-18.37%	-2.41	-0.49%	-5.65	-0.32
Yorks. & Humber	-1.56	10.21%	-2.23	0.20%	-4.55	0.40%

Note: The table shows the share of the change in the labour share that is attributable to changing market power and industry concentration. This is calculated as the effect of the change in market power and industry concentration, derived from specification 6 in table 3.4, divided by the overall change in market power in the region. Labour share change in percentage points. Observations are weighted by survey designed weights (a-weight and g-weight) and log employment. LS indicates the labour share.

Chapter 4

Technological invention and local labour markets: Evidence from France, Germany and the UK

4.1.Introduction

With a returning interest in industrial strategy, many governments seek to foster technological invention as a local economic development strategy. The rationale behind this policy approach is two-fold: On the one hand, it is a well-established fact in economic theory that technological progress drives economic growth in the long run (Aghion & Howitt, 1988). On the other hand, innovative and high-tech sectors have multiplier effects (Moretti, 2012). Through their spending on local services, highly paid workers at innovative firms generate further jobs in the local economy, in particular for non-graduates. Therefore, when assessing the local labour market effects of innovation, many scholars focus on the impact of the number of high-skilled workers on other employment (e.g. Kemeny & Osman, 2018; Lee & Clarke, 2019; Lee & Rodríguez-Pose, 2016). However, there is less evidence on the direct impacts of invention and innovation activity on local labour markets, other than mediated through employment multipliers.

Classical models have focused on a dichotomy between "high" and "low" skilled workers. However, recent evidence of routine-biased technical change suggests that jobs in the middle of the income distribution are declining, as they often comprise of routine activities that are easily automated (Autor, 2019; Goos et al., 2014; Harrigan, Reshef, & Toubal, 2021). Yet, technological invention may also provide a source of job growth for mid-skilled workers in occupations that require creativity and soft skills (Aghion, Bergeaud, Blundell, & Griffith, 2019). There is little evidence of the local labour market effects of innovation on employment by level of education, a gap that this study seeks to fill.

This chapter studies the effects of technological invention, measured by patent filings, on regional employment in France, Germany and the UK. I distinguish between three skill groups, graduates, all non-graduates, as well as those with advanced vocational qualifications below degree level (henceforth also called "mid-skilled"). I estimate these effects with the help of panel data analysis for the period between 2000 and 2019 at the level of NUTS1 and NUTS2 regions. I use local projections estimation (Jordà, 2005) to trace out the effects of changes in patenting and graduate employment on non-graduate and mid-skilled employment over a period of one to six years and calculate multiplier effects of the additional jobs created. I also investigate heterogeneity across the three countries in the sample. While these three large, developed economies are the most innovative in Europe in terms of patent filings, they are very different in terms of their innovation systems and labour market institutions.

The study contributes to the large literature on innovation-employment multipliers (Brenner, Capassi, Duschl, Frenken, & Treibich, 2018; Eberle, Brenner, & Mitze, 2020; Frocrain & Gitraud, 2018; Kemeny & Osman, 2018; Lee & Clarke, 2019; Moretti, 2010; Moretti & Thulin, 2013; Van Dijk, 2018; Van Roy, Vértesy, & Vivarelli, 2018). In contrast to the previous literature, the chapter considers and compares the effects across three countries. The results show considerable heterogeneity across countries that can be explained by differences in labour market institutions. The estimation strategy provides the adjustment in employment in response to shocks over several years, rather than a single point in time. While growth in graduate employment is relatively persistent, gains in non-graduate and mid-skilled employment tend to be short-lived, with employment reverting to the baseline within two to three years.

The chapter proceeds as follows: Section 4.2 reviews the relevant literature and introduces the theoretical framework underlying the analysis. Section 4.3 describes the dataset and introduces the estimation strategy. Section 4.4 provides the results. The chapter is exploratory in nature and there are several limitations that warrant further investigation. These are discussed in section 4.5.

4.2. Related literature and theoretical framework

In the following, I briefly review the literature on the labour market impacts of innovation, situating this in the contexts of the three countries studied. While the empirical analysis focuses on technological invention proxied by patenting, I will use the term "innovation" loosely below, as definitions differ. The shortcomings of relying solely on patents as a measure of invention are discussed in section 4.3. I conclude the discussion of the literature with a simple theoretical framework that guides the following analysis.

4.2.1 Innovation multiplier effects

The idea that employment creation in some sectors increases employment in others has been well established for a long time (North, 1955). Theory predicts that tradable industries create employment in non-tradable industries, either through direct links such as local distribution and business services, or indirectly, through the consumption of local services by those employed in the tradable industry (Moretti, 2012). Recent evidence confirms the significance of the multiplier effect for regional growth (Frocrain & Gitraud, 2018; Moretti, 2010; Moretti & Thulin, 2013), although its magnitude remains somewhat disputed (Van Dijk, 2018).

In this context, innovation plays an important role because of the rents that creators of new ideas are able to capture. Innovation relies on highly skilled workers who share part of these rents (Kline et al., 2019; Van Reenen, 1996). The comparative advantage that innovative firms enjoy allows these firms to grow, leading to higher employment at the individual firm level (Balasubramanian & Sivadasan, 2011; Van Roy et al., 2018).

Wider regional effects of innovation are generally conceptualised in terms of consumption multipliers. In this respect, innovative industries are not very different from other industries relying heavily on high-skilled, highly paid workers, such as knowledge-intensive business services (Brenner et al., 2018). Indeed, there is evidence that these industries contribute to the polarisation of labour markets by creating a lot of employment in local service industries (Kemeny & Osman, 2018), jobs that are often low paid (Lee & Clarke, 2019).

However, the effects of innovation can go beyond the consumption channel, as successfully innovating firms fuel further research and development activity at the regional level, and create further employment in innovative industries (Buerger, Broekel, & Coad, 2012). Innovative regions attract graduates that contribute to a virtuous cycle of innovativeness, employment growth, and human capital accumulation (Faggian & McCann, 2009). Yet, innovation may contribute to growing polarisation between innovative, fast-growing regions that attract skilled workers, and those that are left behind (Autor, 2019; Rodríguez-Pose, 2018).

Nonetheless, innovation may also benefit those with qualifications below degree level (Filippetti & Guy, 2016). After all, not all workers involved in innovation and innovative industries are high-skilled. Aghion et al. (2019) find that low-skilled workers benefit from innovation at the firm level in terms of higher wages, in particular in jobs reliant on soft skills. Polarisation of labour markets with growth concentrated in both high- and low-paid non-routine occupations has been driven by skill-biased technical change and offshoring which has eliminated many mid-skilled routine occupations in high-income economies (Autor & Dorn, 2013; Caselli & Manning, 2017; Goos et al., 2014). In contrast to low-skilled occupations, mid-skilled occupations that were lost in manufacturing sectors have not been replaced in the service economy.

By virtue of their newness, tasks in innovative industries are less likely to be automatable, at least in the medium term. Following a successful innovation, the composition of new hires tends to reflect a firm's previous skill profile, indicating no evidence of a skill bias of technological change at the firm level (Kline et al., 2019). This is also supported by theories of industry life cycles, whereby industries are most agglomerated during the most innovative stages before offshoring and outsourcing take over in more mature phases (Audretsch & Feldman, 1996a). However, the degree to which benefits of innovation are shared across skill groups depends on the institutional and wider policy environment (Bramwell, 2021; Ciarli, Marzucchi, Salgado, & Savona, 2018).

While innovation may be a source of employment growth, skilled workers are also an important input in the innovation process (Faggian et al., 2017; Gagliardi, 2014), and collaborations between universities and industry are a driver of local innovation (Crescenzi, Filippetti, & Iammarino, 2017; D'Este, Guy, & Iammarino, 2013). Regions with abundant human capital therefore attract innovative activities, which may reinforce inequalities between regions. Furthermore, innovative industries tend to cluster more than other industries (Audretsch & Feldman, 1996b). This is because of the strong path dependency in knowledge creation and the small radius in which knowledge spillovers tend to occur (Sonn & Storper, 2008). Where exactly innovative activities locate and thrive remains a topic of intense scholarly debate, with factors including local and national institutions, skills and serendipity all playing a role (Chatterji, Glaeser, & Kerr, 2014; Storper et al., 2015). While lagging regions need to invest in innovation to catch up with leaders, they often lack the absorptive capacity to do so, further widening the divide (Muscio, Reid, & Rivera Leon, 2015).

4.2.2 National innovation and education systems

The three countries included in the empirical analysis are deliberately chosen to represent different industrial structures and national and regional institutions. Theories of regional systems of innovation emphasise the importance of local actors, institutions and path dependency (Iammarino, 2005). These systems interact directly with labour market institutions, in terms of the skill profile of the workforce and the incentives for businesses to be innovative. Among the three countries, France has the most stringent employment protection laws, while the UK has the most liberal. German labour market institutions resembled the French, but have been somewhat liberalised in recent years (Griffith & Macartney, 2014).

There are also significant differences in terms of education systems. Germany has a strong tradition of vocational post-secondary education of the "dual apprenticeship" model, whereby apprentices spend some time acquiring firm-specific skills while training on the job, and the rest of their time acquiring transferable skills at a further education college. In contrast, while the French education model also provides a range of post-secondary qualifications below degree level, skills tend to be acquired on the job with company-based training. In the UK, further education is weak, with mostly college based training (Esteves-Abe, Iversen, & Soskice, 2001). Instead, access to higher education has been promoted, so that the share of university graduates in the workforce is highest in the UK, as I will show below.

These differences have important implications for the level and type of innovation. Generous unemployment insurance gives workers confidence to acquire specialised skills, as is the case with the German and French further education systems. The wider diversity of skills that these economies possess is conducive to innovation (Filippetti & Guy, 2020). On the other hand employment protection legislation that makes it harder to hire and fire workers may provide an incentive for firms to innovate to improve productivity in an otherwise inflexible setting. However, rigid institutions also make workforce adjustment harder if skill requirements change due to technological progress. The evidence suggests that there is more innovation overall in countries with stronger employment protection, but this tends to be incremental, whereas countries with liberal labour market institutions tend to be drivers of radical innovation (Griffith & Macartney, 2014).

Institutions also affect the degree and speed of adjustment following a technological shock. The multiplier effect identified above may be less pronounced if hiring is costly or workers lack the right skills to fill roles. Highly specialised skills make it harder to adjust in the face of technological and organisational change (Lamo, Messina, & Wasmer, 2011). Internal migration provides an important adjustment mechanism to fill jobs in regions with high labour demand due to innovation (Bartik, 1993; Faggian & McCann, 2009). However, the mobility of the labour force is again dependent on the flexibility of labour market institutions, whereby inflexible institutions provide an obstacle to mobility (Monastiriotis & Sakkas, 2021). As shown in chapter 2, internal migration in itself can also affect local labour markets.

4.2.3 Theoretical framework

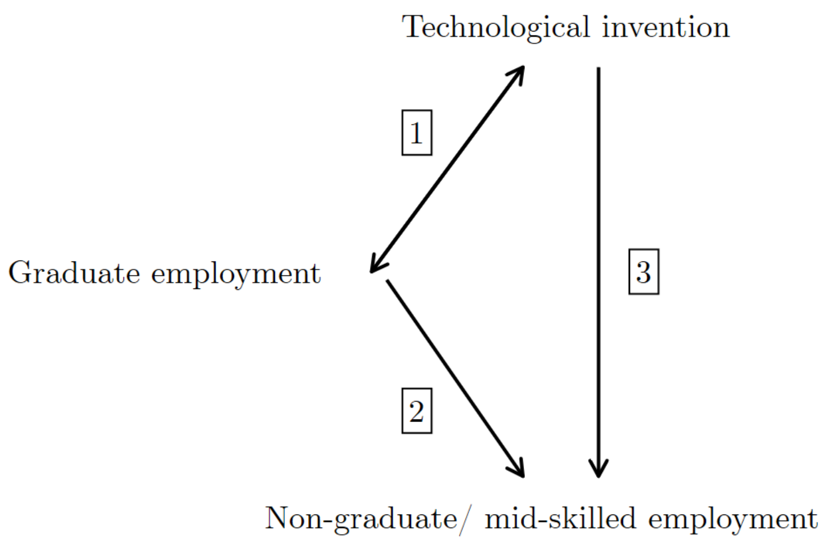
To summarise, technological invention is an important driver of local employment growth. However, there are several sources of growth. Inventions may contribute to income growth, and in turn increase consumption of local services. Additionally, innovating firms may expand their workforce, hiring more mid- and high-skilled workers to expand production and innovate further. All this is mediated by labour market institutions which dictate the costs of hiring and firing, as well as the local skill mix available to businesses.

Figure 4.1 translates this into a simple framework underpinning the following analysis. The interdependence of invention and graduate employment (1) is already well documented in the literature. Equally, there is evidence of the multiplier effect of graduate on non-graduate employment (2). However, there is less evidence of the effect of technological invention on employment for people without a university degree or with vocational qualifications. These effects are especially important given a general trend towards the decline of mid-skilled jobs (Autor, 2019; Goos et al., 2014; Harrigan et al., 2021). The question is whether technological invention can halt some of this decline. At the macroeconomic level, theories of skill-biased technological change predict a negative effect of innovation on low-skilled employment (Machin, 2001). At the local level, these effects may be different. Innovative activity may be less prone to automation, as it is non-routine by nature. At the beginning of the product or industry life cycle, production is less likely to be offshored and more likely to be kept close to the development site (Audretsch & Feldman, 1996a).

The effect of graduate employment on non-graduate employment is generally conceptualised as a consumption channel. Highly skilled and highly paid workers consume local services, which creates jobs for non-graduates. If technological invention has a positive effect on graduate employment, this also creates an indirect effect from invention to non-graduate employment. However, there may be direct complementarities between non-graduates and both graduate employment and invention. Non-graduates are not a homogenous group, with many possessing advanced qualifications below degree level. Those with vocational and technical qualifications may be employed in occupations adjacent to innovative firms and industries, such as within research labs or prototyping and manufacturing.

The next section introduces the data used in the analysis, which provides estimates of the number of graduates, all non-graduates and a mid-skilled group with advanced vocational qualifications at the regional level for France, Germany and the UK. The aim of the estimation strategy is to estimate effects (1), (2) and (3) in figure 4.1, between graduate employment and technological invention and of those two variables on non-graduate and mid-skilled employment.

Figure 4.1: Theoretical framework



4.3.Data and empirical methods

The goal of the chapter is to estimate the relation between patenting as a proxy for technological invention and employment for different skill levels at the regional level in France, Germany and the UK. The following sets out the development of a dataset that is consistent across countries and over time.

4.3.1 Measuring technological invention

The OECD REGPAT database provides patents matched to NUTS regions, which can be used as a measure of local inventions (OECD, 2021). The database covers all patents filed with the European Patent Office (EPO) as well as those filed under the Patent Co-operation Treaty (PCT) after 1977. Following Sonn and Storper (2008), I use the inventor location to assign patents to a region, as this is most likely where the innovative activity has taken place. If there are multiple inventors in different regions, the patent is counted fractionally. The number of patents applied for during a given year by local inventors is then the measure of regional innovativeness. While the application date is used as the date of the invention, only applications that are ultimately successful are included in the dataset.

Patents are a noisy measure of invention. On the one hand, many patents are not very valuable commercially (Hall, Jaffe, & Trajtenberg, 2001; Pakes, 1984). On the other hand, many valuable ideas are not or cannot be patented for various reasons. Patents apply mainly to product innovation, and therefore do not measure process innovation. They only represent the first stage in the innovation process, with many inventions never making it to the next stage of commercialisation (Carlino & Kerr, 2015). The further innovation process after the registration of a patent may also take place in a different location from the invention itself (Feldman, 1994). Patents are less applicable to service industries, although patents can be granted for software code. Nonetheless, in cross-country comparisons, patents capture variation in research productivity (de Rassenfosse & van Pottelsberghe de la Potterie, 2009), and have direct impact on firm-level employment, productivity and wages (Kline et al., 2019; Van Reenen, 1996).

4.3.2 Employment by education levels

The challenge with measuring employment by educational attainment lies in the diversity of educational systems and qualifications used across the three countries, in particular above the secondary level. There is a trade-off between availability of finer grained regional data and more detailed educational information. Therefore, the analysis relies on two different datasets.

The first dataset, provided by Eurostat, provides employment by broad educational attainment at the NUTS2 regional level. The classifications available are tertiary, upper secondary, and primary or lower secondary. I summarise the latter two as non-graduates, while those with tertiary education are deemed graduates. The graduate category is somewhat vaguely defined and considers different levels of post-secondary education for different countries, including apprenticeships and college courses, other than university degrees. Consistent estimates for the three countries are available from 1999 to 2019. The classification is a very rough approximation of skill levels. It is noticeable that the share of graduates in Germany is overall lower than that in Great Britain or France as vocational degrees are more prevalent.

The second dataset uses the European Social Survey (ESS) to construct an intermediate group with advanced vocational education, to distinguish these workers from those

Table 4.1: Definition of the intermediate education category

France	Germany	UK
First university degree (premier cycle)	Master craftsman, technician or equivalent college diploma	Nursing certificate
Elementary diplomas in law and pedagogy	Apprenticeship in commerce, industry, crafts or agriculture	Teacher training
Professional and technical vocational degrees (brevet)	College degrees in pedagogy, nursing and other medical assistant professions	Technical diplomas
	Elementary civil service exams (Laufbahnprüfung)	

Note: National qualifications included in the ISCED IV – advanced vocational, sub-degree category. Includes most relevant categories only.

with a university degree. The ESS is a household survey that has been conducted every two years since 2002, providing nine survey waves to date. The survey asks respondents about their educational attainment as well as – if applicable – that of their partner. Responses are coded to the International Standard Classification of Education (ISCED), but the original responses according to national standards are also provided. The level of detail and classifications available varies over time, also in response to changes in national education systems. As a baseline, I use ISCED IV – advanced vocational, sub-degree – as the definition for the intermediate education category. For more recent surveys, all education levels are coded to harmonised ISCED levels. However, in the four surveys between 2002 and 2008, this is not always the case and gaps have to be filled manually. Table 4.1 gives an overview of the qualifications making up the intermediate category.

While the ESS is a household survey and responses are available at the individual level, these can be aggregated into regional totals. Geographical information is available at the NUTS1 level, i.e. larger regions than the NUTS2 regions available on the Eurostat dataset. To make full use of the available data, I consider both respondents as well as information available on their partners so that the total working population is made up of working respondents and working partners of respondents. Partners are assigned the same weight as respondents. In some regions, there is a lot of fluctuation in sample sizes between waves of surveys, resulting in even larger variations in the number of those with vocational qualifications. To reduce the survey variation, I normalise the number of employees by total Eurostat employment according to equation 4.1, multiplying the raw number of mid-skilled workers, $emp^{mid-raw}$ as a share of total employment in the ESS, emp^{ESS} by total employment from Eurostat. This normalisation is not required for the non-graduate and graduate variables, as these are available as aggregated population totals. As NUTS2 regions are nested in NUTS1 regions, it is easy to aggregate variables available from Eurostat into the NUTS1 regions available on the ESS, so that all variables used in the analysis involving ESS variables are at the same regional level.

$$emp^{mid} = \frac{emp^{mid-raw}}{emp^{ESS}} * emp^{Eurostat} \tag{4.1}$$

The ESS provides a more detailed categorisation of education and qualification levels than the Eurostat dataset. However, the limited number of survey waves available makes it difficult to conduct time series analysis using the dataset. Therefore, I only use the ESS dataset to estimate the intermediate skill category, which is not available from Eurostat.

4.3.3 Estimation strategy

Estimating the effects of innovation on regional employment is challenging because of the endogeneity of all variables involved. Innovation may create jobs, but also depends on the availability of local skills. Furthermore, high-skilled workers may be directly responsible for the creation of lower-skilled jobs through the consumption channel. I rely on the panel aspect of the data to deal with these issues. As outlined above, I expect that graduate employment depends on innovation and that non-graduate and mid-skilled employment depend on both innovation and graduate employment.

For all variables, I estimate the effect over increasing time horizons to trace the cumulative effect of the explanatory variables over time, following the local projections approach by Jordà (2005). The method can be used to estimate impulse response functions for multivariate dynamic systems, similar to vector autoregression (VAR). Indeed, many studies use VAR estimation in similar contexts (e.g. Brenner et al., 2018; Buerger et al., 2012; Eberle et al., 2020). However, among other advantages, the estimates are more robust to misspecification and can be estimated by OLS (Jordà, 2005). While a VAR relies on extrapolation of impulse responses from lagged effects, the local projection method explicitly estimates effects at different forecast horizons. Other studies estimate multiplier effects for single points in time (e.g. Kemeny & Osman, 2018; Lee & Clarke, 2019). However, that approach cannot reveal information about the dynamics of the multiplier effect. As I will show below, the effect can take some time to materialise, and also disappear again after a few years.

Equation 4.2 specifies the estimating equation for the effect of patenting on graduate employment growth. $emp^{g}_{r,t+h} - emp^{g}_{r,t-1}$ is the log difference in graduate employment in region r between $t-1$ and $t+h$. pat_{t-1} is the number of patents filed in t-1 in logs, $emp^{g}_{t-1,t-2}$ are lags of the dependent variable, and $X_{r,t}$ are additional control variables. In particular, I control for population density and a dummy variable equal to 1 in 2009 and 2010 during the recession following the financial crisis. Region fixed effects α_r control for unobservable differences in regions that are invariant over time. Of particular concern are differences in economic structures with some regions specialising in industries that are innovative, but less prone to patenting, such as software development and service industries. These structural characteristics of regions change relatively slowly, so that fixed effects control for this.

$$emp^{g}_{r,t+h} - emp^{g}_{r,t-1} = \beta_0 + \beta_h pat_{r,t-1} + emp^{g}_{r,t-1,t-2} + \gamma X_{r,t} + \alpha_r + \epsilon_{r,t} \tag{4.2}$$

I estimate this model for h running from -4 to 5 to trace out the effect of patenting on employment over time. The negative lags test for a placebo effect: If there was already an effect detectable before the patenting shock occurs, it would suggest that an underlying unobserved variable is causing both the patenting and the graduate employment shock. To visualise the impulse response, I plot the β_h against the time horizon effectively tracing the cumulative effect of the patenting shock over time.

Effects on the other variables are estimated analogously. Equation 4.3 specifies the effect of graduate employment and patenting on non-graduate employment. Here, non-graduate employment growth, $emp^{ng}_{r,t+h} - emp^{ng}_{r,t-1}$ is estimated as a function of graduate employment growth, where Δemp^{g}_{t-1} is the log difference in graduate employment between t-1 and t-2, and the number of patents filed in a year, pat_{t-1}, in logs.

$$emp^{ng}_{r,t+h} - emp^{ng}_{r,t-1} = \beta_0 + \beta^{g}_{h} \Delta emp^{g}_{r,t-1} + \beta^{p}_{h} pat_{r,t-1} + emp^{ng}_{r,t-1,t-2} + \gamma X_{r,t} + \alpha_r + \epsilon_{r,t} \tag{4.3}$$

The estimating equation for higher vocational or mid-skilled employment, equation 4.4, accounts for the fact that employment estimates in this category are only available in two-year intervals as explained above. Graduate employment is included as the two-year growth rate and patenting as the total over two years. I estimate this equation for h running from -3 to 3.

$$
\begin{aligned}
emp^{mid}_{r,t+2h} - emp^{ng}_{r,t-2} = \beta_0 + \beta^g_h \Delta emp^g_{r,t-2} + \beta^p_h (pat_{r,t-1} + pat_{r,t-2}) \\
+ \Delta emp^{mid}_{r,t-2} + \gamma X_{r,t} + \alpha_r + \epsilon_{r,t} \quad (4.4)
\end{aligned}
$$

As noted before, causal identification of these effects is challenging, because of the interdependence of the variables. The placebo test checks for reverse causality, as changes in the dependent variable cannot feasibly be caused by future changes in the explanatory variable. However, missing variable bias is undetected if both the changes in the dependent and explanatory variable are caused by a different, unobserved variable or shock. Instrumental variables (IV) can be used to overcome this problem, but it is difficult to find instruments that are applicable in the different country contexts. For example, Lee and Clarke (2019) use the historical location of art and design schools to predict the current share of high-tech employment in the population. Given the different histories, such historical instruments would not be appropriate for the three countries studied here. The inclusion of lagged dependent variables can alleviate some of these concerns, as this controls for a general trend in the dependent variable that might at the same time affect the explanatory variable, such as a general improvement in the business environment of a region.

4.4.Results

4.4.1 Descriptive analysis

Table 4.1 provides summary statistics for the estimation sample by country. The observations in this table are at the regional level. As explained above, Eurostat-based variables and patents are at the NUTS2 level, while ESS-derived variables are at the NUTS1 level and only available every second year. Overall, there are 96 NUTS2 regions, 21 in France, 38 in Germany and 37 in the UK. A small modification was made to the standard NUTS2 regions, by combining the five NUTS2 regions that make up Greater London into one. This is appropriate, as Greater London can be viewed as a single labour market area.

Correspondingly, the Île de France region around Paris is a single NUTS2 region. There are 41 NUTS1 regions, 13 in France, 16 Germany and 12 in the UK.

The most significant differences across countries are in terms of patenting activity. There are on average 728 patent applications per NUTS2 region and year in Germany, but only 202 in the UK. French regions are in the middle, with 471 applications. However, the standard deviation is largest in France, suggesting a more unequal distribution. These differences are repeated at the NUTS1 level at a larger scale, given the higher aggregation of the data.

Regions differ slightly in average size across countries, so employment figures by educational attainment are not directly comparable. As a share of total employment, graduate employment is highest in the UK at 36% on average across NUTS2 regions (NUTS1: 37%), followed by France at 33% (NUTS1: 35%). The graduate employment share is markedly lower in Germany, at only 27% (NUTS1: 27%). In contrast, the share of employees with advanced vocational qualifications is higher in Germany, at 19% on average across NUTS1 regions, compared to 16% in France and 15% in the UK.

Table 4.2 shows some characteristics of employees by educational attainment, derived from the ESS micro data. The table confirms that the higher vocational category accurately captures an intermediate income and skill group. It shows average earnings, years of education, and other job attributes for the intermediate skill group with a higher vocational qualification as explained above, as well as other groups with no degree, a university degree, and advanced degree, such as an MSc or a professional diploma. Not all questions are asked in every wave of the survey, which is why the sample size varies substantially between questions. These variables are not used in the analysis, but rather to characterise the different skill groups. As these groups are defined by completed level of education rather than occupation, there is a risk of mismeasurement if many work in jobs that they are over or under-qualified for. Reassuringly, the income and other characteristics reported in the following confirm significant differences across educational groups.

Gross pay is only measured in 2004. As expected, average earnings for workers with intermediate educational attainment sits in between workers with and without a university degree. A household's net income decile is reported every year. Note that this also takes income of other household members into account and is therefore less closely related to the respondent's educational attainment. Nonetheless, the pattern is similar to gross income, in that workers with intermediate education are on average in higher income deciles than

Table 4.1: Summary statistics

	Full sample		France		Germany		UK	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
NUTS2 level								
Patents	472	667	471	817	728	748	202	214
Graduate employment	309	321	395	471	277	172	290	322
Non-graduate employment	666	424	805	584	740	361	502	302
Total employment	986	721	1201	1036	1028	524	811	618
Population density	447	787	148	196	452	725	624	993
N	1749		399		694		656	
NUTS1 level								
Patents	1091	1709	912	1131	1583	2326	566	486
Graduate employment	777	581	834	592	651	588	903	533
Advanced vocational emp.	410	366	378	205	462	504	363	194
Total employment	2411	1687	2362	1189	2399	2243	2462	1017
Population density	569	1061	207	281	676	1041	694	1359
N	332		80		144		108	

Note: Observations are year x region. Variables at the NUTS2 level are for 2000-2019. Variables at the NUTS1 level for even numbered years between 2002 and 2018. All employment numbers are in thousands. Advanced vocational employment at the NUTS1 level is derived from ESS and normalised to total regional employment. Population density is measured in persons per square kilometre.

Table 4.2: Descriptives for educational categories in ESS

	Higher vocational		No degree		Degree		Advanced degree	
	Mean/SD	N	Mean/SD	N	Mean/SD	N	Mean/SD	N
Gross pay	10681.5	859	7097.4	3405	18312.1	1196	17931.5	466
	(23575.1)		(18936.4)		(30266.3)		(34124.4)	
Househ income decile	6.79	4915	6.07	18114	7.62	7796	7.69	3557
	(2.38)		(2.50)		(2.29)		(2.33)	
Years of education	14.9	5683	12.8	21276	17.4	9141	18.4	3936
	(2.61)		(2.69)		(3.14)		(3.07)	
Working hours	40.8	5632	38.6	21055	41.3	9040	42.3	3890
	(12.4)		(13.1)		(12.4)		(12.3)	
Job requires >basic edu	0.79	1023	0.59	4136	0.90	1447	0.92	557
	(0.41)		(0.49)		(0.30)		(0.27)	
Job requires learning	2.99	1030	2.65	4200	3.16	1453	3.11	557
	(0.95)		(1.04)		(0.88)		(0.87)	
Has partner	0.68	5704	0.66	21385	0.67	9181	0.69	3957
	(0.47)		(0.48)		(0.47)		(0.46)	
N	5704		21385		9181		3957	

Note: ESS rounds 1-9 (2002-2018) for France, Germany and the UK. Includes information on respondents only. Gross pay only available for round 2 (2004). Household income decile only available for rounds 4-9 (2008-2018). Dummy variable asking whether current job requires more than basic education only available for rounds 2 and 5 (2004 and 2010). Variable asking whether job requires learning new things (coded 1 = Not at all true to 4 = Very true) only available for rounds 2 and 5 (2004 and 2010). Years of education and working hours available for all rounds. Partner is also available for all rounds and indicates whether respondent has a partner for whom employment and educational attainment are also available.

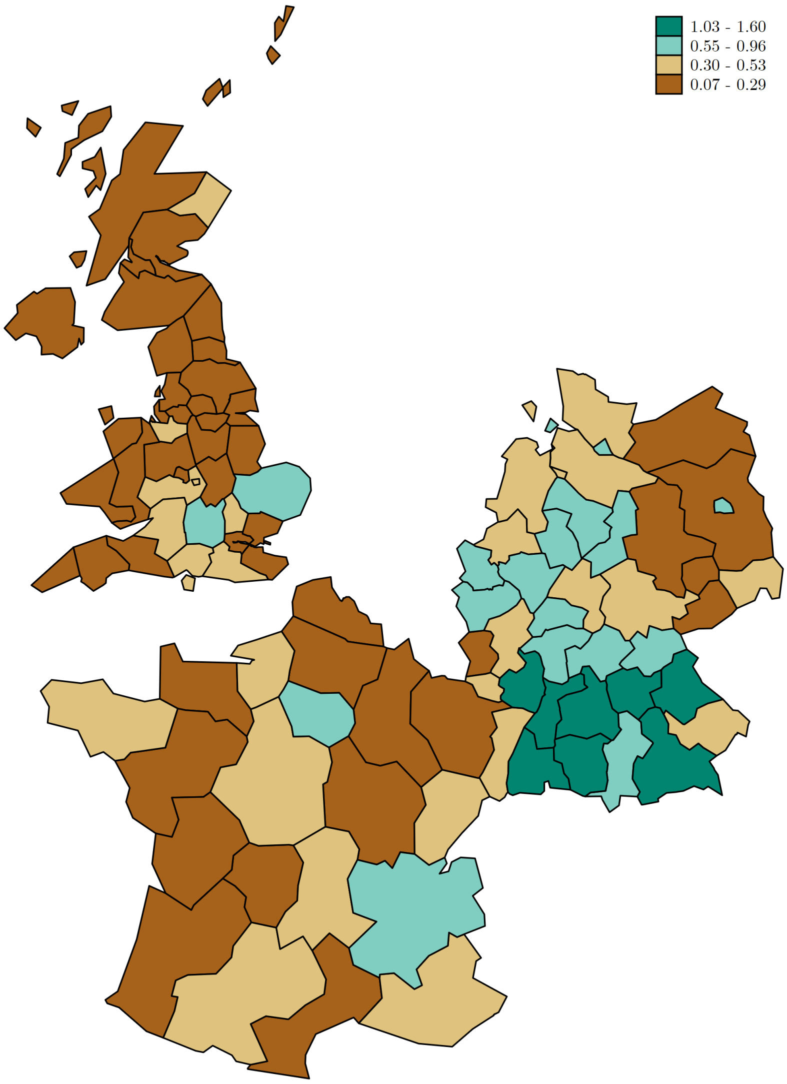
workers without a degree, but in lower deciles than workers with a degree. The share of respondents with a partner is reported at the bottom of the table, as this might be driving differences in household income. The differences across education groups are not significant, although there might still be differences in partners' educational attainment or propensity to work. Hours worked are roughly similar across education groups, albeit slightly lower for less and slightly higher for more educated workers.

In terms of years of education completed, the intermediate category also falls neatly between graduates and non-graduates, with 14.9 years on average. In 2004 and 2010, respondents were asked whether someone applying for their job would require more than compulsory education. Among those with an advanced vocational qualification, 79% responded yes, while this was only the case for 59% of workers with no degree, but 90% of workers with a degree. Workers were also asked whether their job requires learning new things. The question was answered on a scale of 1 to 4, where 1 is "Not at all true" and 4 is "Very true". Again, the average answer for the intermediate education group is in between those with and without a degree.

Figure 4.1 shows the average annual number of patent applications per 1000 employees at NUTS2 level. The rate of successful applications is highest in the south of Germany. This is in contrast to low levels of patenting in most regions in the east. In France, the rate of patenting is highest in the Île-de-France and Rhône-Alpes regions. As discussed above, patenting is overall lower in the UK, with the regions around Oxford and Cambridge having the highest rates of patenting. While London is performing well in absolute terms, the rate of patenting is small relative to total employment.

The next figures explore basic correlations between patenting and employment growth for different education groups. Figure 4.2 plots average annual growth in non-graduate employment against total patenting over the observation period. The relationship is positive, if loose. The high-performing German regions of Oberbayern, Stuttgart and Düsseldorf, but also London, are close to the regression line. It should be stressed that these regions have highly successful, knowledge intensive economies overall, so that the correlation with patenting cannot be considered evidence of a causal relationship. On the other hand, the Île de France has seen among the highest rates of losses in non-graduate jobs. Overall, growth in non-graduate jobs is relatively low in France, both in highly innovative regions, such as Rhône-Alpes, as well as less innovative and more remote regions like Limousin. In the UK, some traditional manufacturing regions like the West Midlands experienced

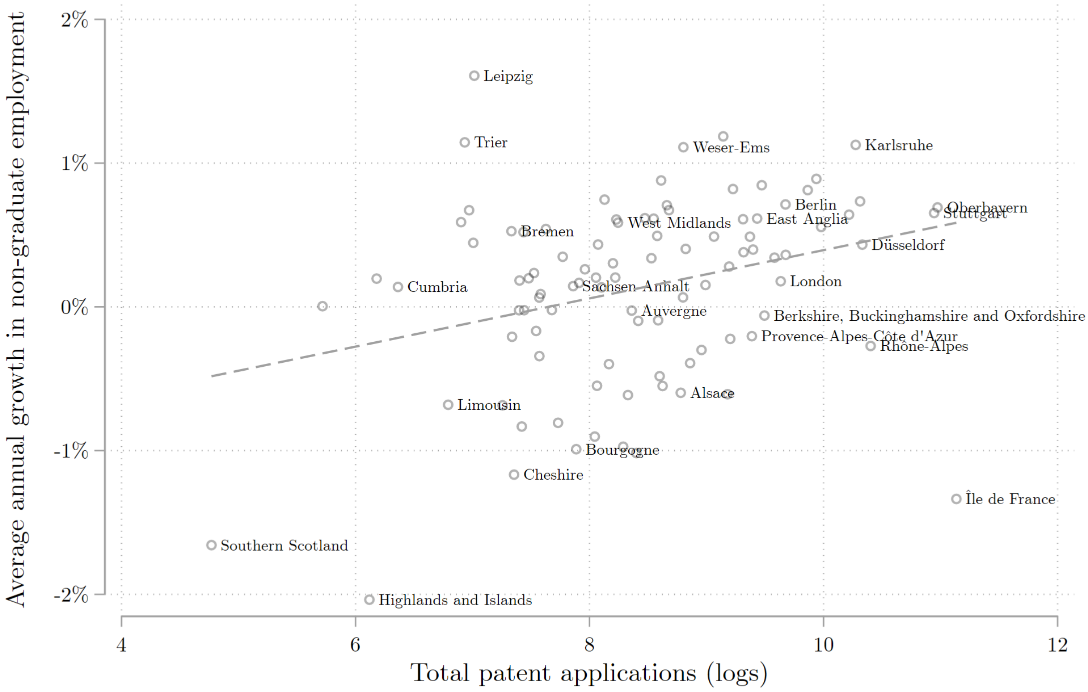
Figure 4.1: Patent applications per 1000 employees



Note: Average for 2000-2017, NUTS2 regions.

strong employment growth, despite being average in terms of innovativeness.

Figure 4.2: Patenting and non-graduate employment growth



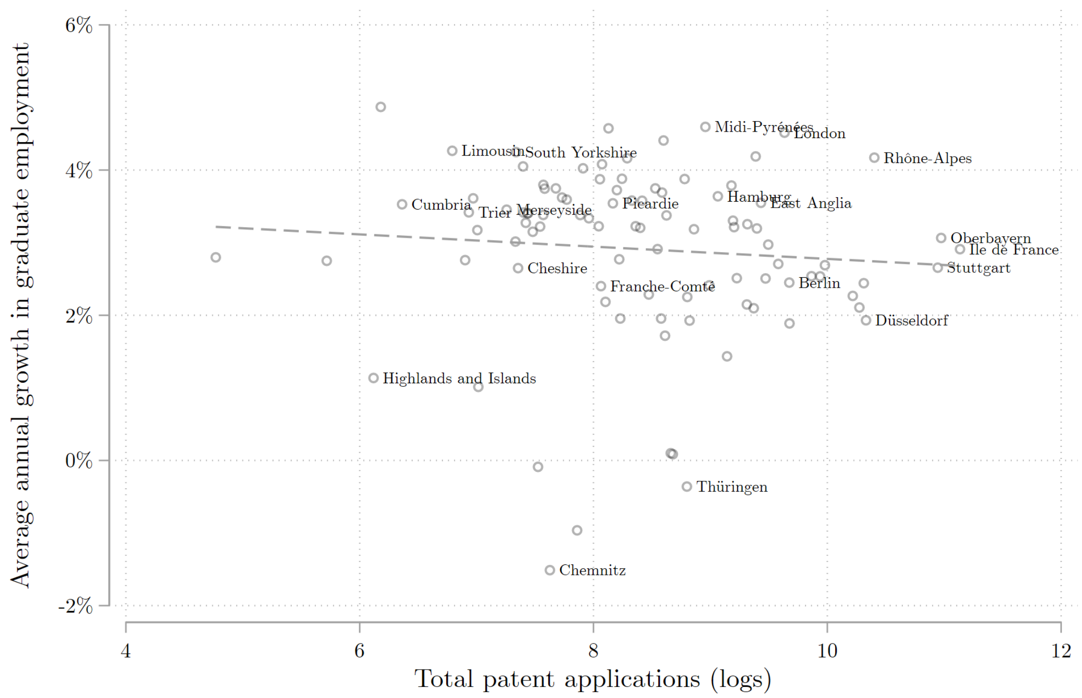
Note: Total patent application for 2000-2018 and average annual employment growth for non-graduates for 2000-2019. Each observation is a NUTS2 region.

In contrast, figure 4.3 shows only a weak, negative unconditional correlation between patenting and graduate employment growth. While employment growth is on average higher for graduates than non-graduates, at around 3% against 0.1%, more innovative regions do not necessarily create more jobs. The following sections test for these relations formally.

4.4.2 Patenting and graduate employment

The first set of results looks at the interdependence of graduate employment and patenting. To visualise the results, figure 4.4 plots the β_h coefficients from equation 4.2. These are the coefficients of lagged patenting in a regression of changes in graduate employment over the time period indicated on the x-axis. Full regression results can be found in appendix table 4.A.1. As the estimation runs over changing time horizons, the y-axis can be interpreted as the difference in employment over the baseline in year t-1.

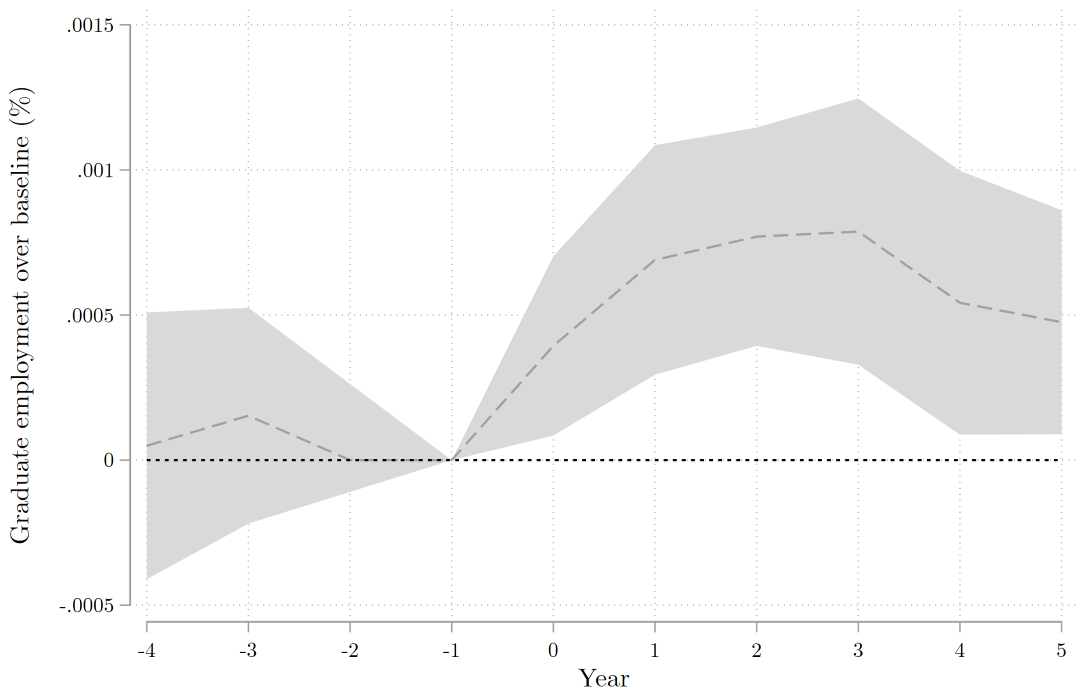
Figure 4.3: Patenting and graduate employment growth



Note: Total patent application for 2000-2018 and average annual employment growth for graduates for 2000-2019. Each observation is a NUTS2 region.

Figure 4.4 shows a statistically significant increase in graduate employment in response to an increase in patenting. A 10% increase in patenting leads to an increase in graduate employment by 0.005%. Graduate employment then remains stable at that level for several years. Note that the there are several possible adjustment channels: the increase in employment could both indicate transitions from unemployment or outside the labour force, as well as in-migration of graduates, either from other regions or from abroad. The employment response remains statistically significant for three years but then peters out, implying that employment reverts slowly back to the baseline. This result makes intuitive sense as inventions are likely to have a shelf-live, giving businesses a boost over several years, but continuous innovation is required to retain this advantage. Before year t-1, there is no statistically significant effect. This is the placebo test: changes in graduate employment in the past are not influenced by future patenting. This could be the case if reverse causality was an issue. Reassuringly, this test suggests this is not the case.

Figure 4.4: Graduate employment response to patenting shock



Note: Plot of β_hs from equation 4.2 against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in table 4.A.1.

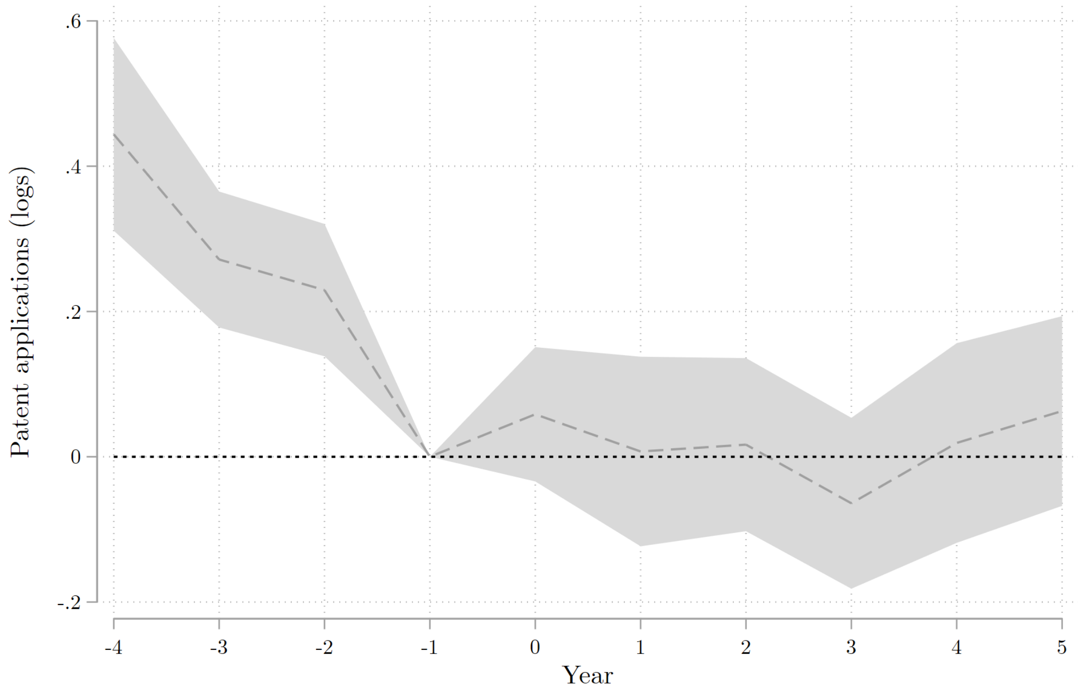
Figure 4.5 confirms that there is no evidence of a reverse effect of changes in graduate employment on patenting. Here, the dependent variable, the number of patents, is in log-levels and the y-axis can be interpreted as the number of additional patents filed between -1 and the time horizon on the x-axis. Full regression results can be found in table 4.A.2 in the appendix. The point estimate hovers around zero and is statistically insignificant throughout. This is not to say that graduates are not important for patenting, and more innovative regions are likely to have a higher share of graduate employment. However, growing graduate employment is not associated with a subsequent increase in patenting. This is in contrast to Faggian and McCann (2009) who find an effect of in-migration of graduates on patenting at the NUTS2 level in the UK. However, they consider recent graduates who migrate upon graduation only, which might constitute a more select group than the general population with a university degree.

In this case, the significant and positive placebo effect is expected: patenting before a graduate employment shock is higher because patenting causes an increase in graduate employment as shown in figure 4.4. The causality runs clearly from innovation to graduate employment, not the other direction. The significant effect from innovation on graduate employment but not in the other direction can be rationalised when considering that most graduates are unlikely to work in the innovative sector directly. Rather, the innovation creates a multiplier effect that creates further jobs in professional services that benefit indirectly from the innovation, such as legal and financial services or marketing and distribution (Moretti, 2012).

4.4.3 Effects on workers without degree and workers with intermediate qualifications

Next, I turn to the employment effects for those without a university degree. I estimate equation 4.3 by regressing the change in non-graduate employment on lagged graduate employment and patenting. The first set of results considers all non-graduates and the regressions are run at the NUTS2 regional level, while further results below consider workers with advanced vocational qualifications. As before, the effects shown in figure 4.8 and 4.9 can be understood as the change in non-graduate employment above the baseline in year t-1 in response to a 1% change in graduate employment or patenting, respectively. Full regression results can be found in table 4.A.3.

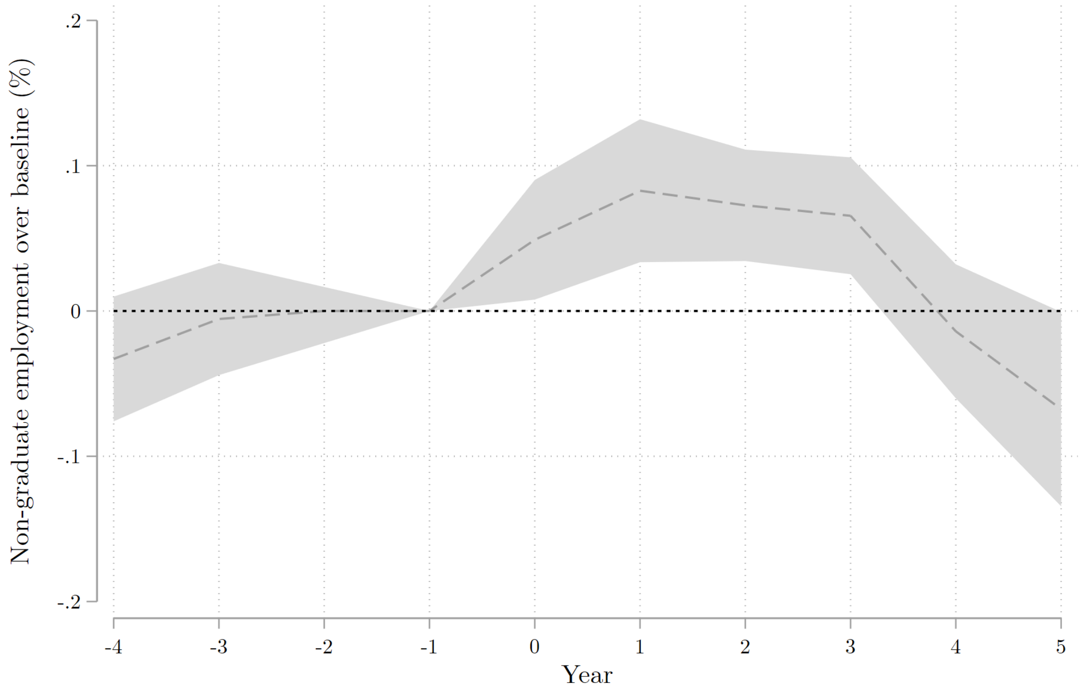
Figure 4.5: Patenting response to graduate employment shock



Note: Results from regression of patenting on lagged graduate employment. The plot shows the coefficients of graduate employment against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in table 4.A.2.

Figure 4.6 shows a significant positive effect of graduate employment on non-graduate employment. Non-graduate employment remains around 0.1% above the baseline for two to three years after an initial 1% increase in graduate employment. The effect is temporary, however, and after four years non-graduate employment reverts back to the baseline. Reassuringly, there is no significant effect before year -1, confirming that there is no evidence of reverse causality.

Figure 4.6: Non-graduate employment response to graduate employment shock

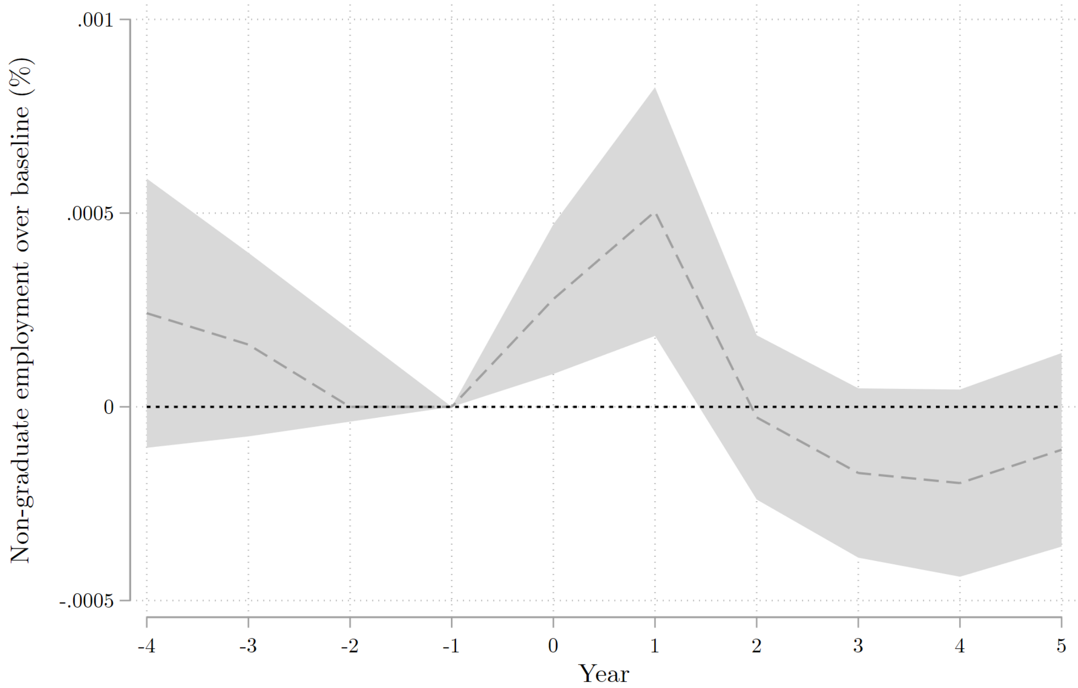


Note: Plot of β_h^gs from equation 4.3 against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in table 4.A.3.

There is a small but short-lived effect of patenting on non-graduate employment, as figure 4.7 shows. Non-graduate employment is significantly above the baseline for two years after the patenting shock, but reverts back to the baseline by year 2, with point estimates turning negative, albeit statistically insignificant. This is expected. The non-graduate category encompasses all workers with less than a bachelor's degree, most of whom are unlikely to be employed in the innovation or associated sectors.

The next set of results zooms in on workers with intermediate, advanced vocational

Figure 4.7: Non-graduate employment response to patenting shock



Note: Plot of β_h^ps from equation 4.3 against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in table 4.A.3.

qualifications that are below degree level. As explained above, mid-skilled employment is only available at two-year intervals and at the NUTS1 regional level, so that the effects shown in figures 4.8 and 4.9 have to be understood in terms of two-year compound growth rates. Full regression results can be found in table 4.A.4. Due to the limited number of survey waves available for the ESS, the sample size varies by time horizon. While this reduces comparability between estimates for different horizons, it makes the best use of the available dataset.

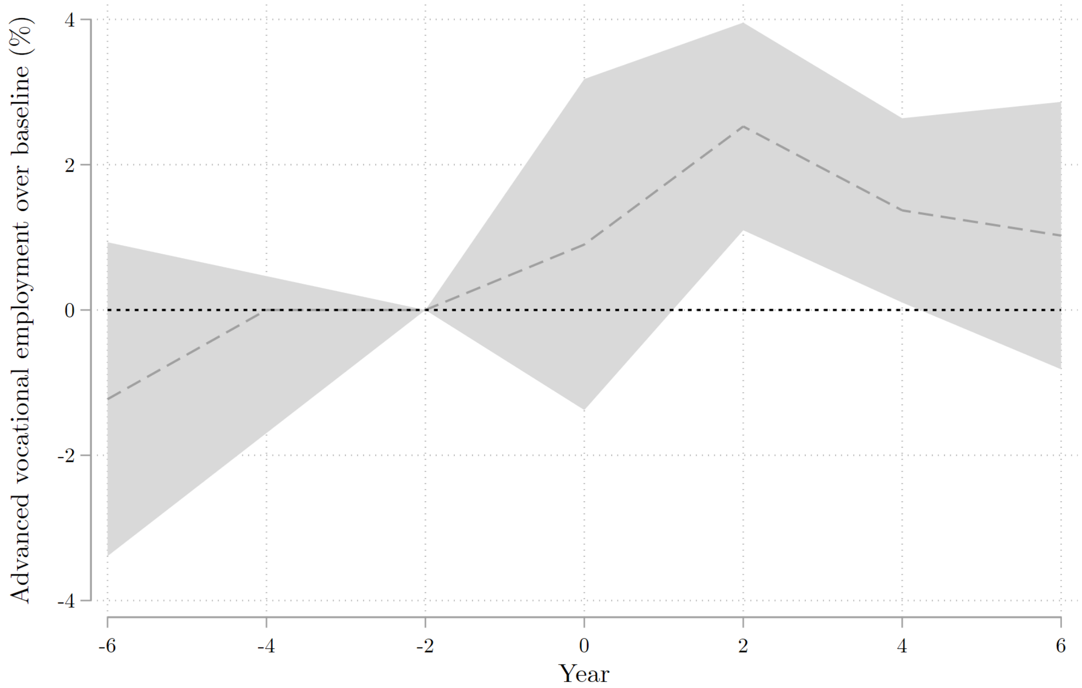
Figure 4.8 shows the effect of graduate employment on mid-skilled employment. After two years, a 1% increase in graduate employment is estimated to lead to a 2% increase over the baseline in year -2 in mid-skilled employment. This effect levels off slightly towards year 6. The effects are larger in magnitude than the effect of graduate employment on all non-graduates shown in figure 4.6. A 1% increase in graduate employment is associated with a 2% increase in mid-skilled employment, compared to 0.1% for all non-graduates. This suggests that the effect for mid-skilled workers may be driven by complementarities with graduates. In contrast, the effect of graduates on non-graduates is usually explained by the consumption of local services by high-paid workers (Lee & Clarke, 2019; Moretti, 2012). While the estimated effects are large, the error bands are also relatively wide. This is to be expected, as employment is estimated from a survey, containing additional sampling variation.

Figure 4.9 shows the effect of patenting on mid-skilled employment. There is a statistically significant immediate positive effect, but employment reverts back to the baseline by year 4. However, the effect is much larger than that for all non-graduates, presented in figure 4.7. This confirms that workers with advanced qualifications below degree level can benefit directly from innovation, not just through the consumption channel from high-skilled workers.

4.4.4 Cross-country heterogeneity

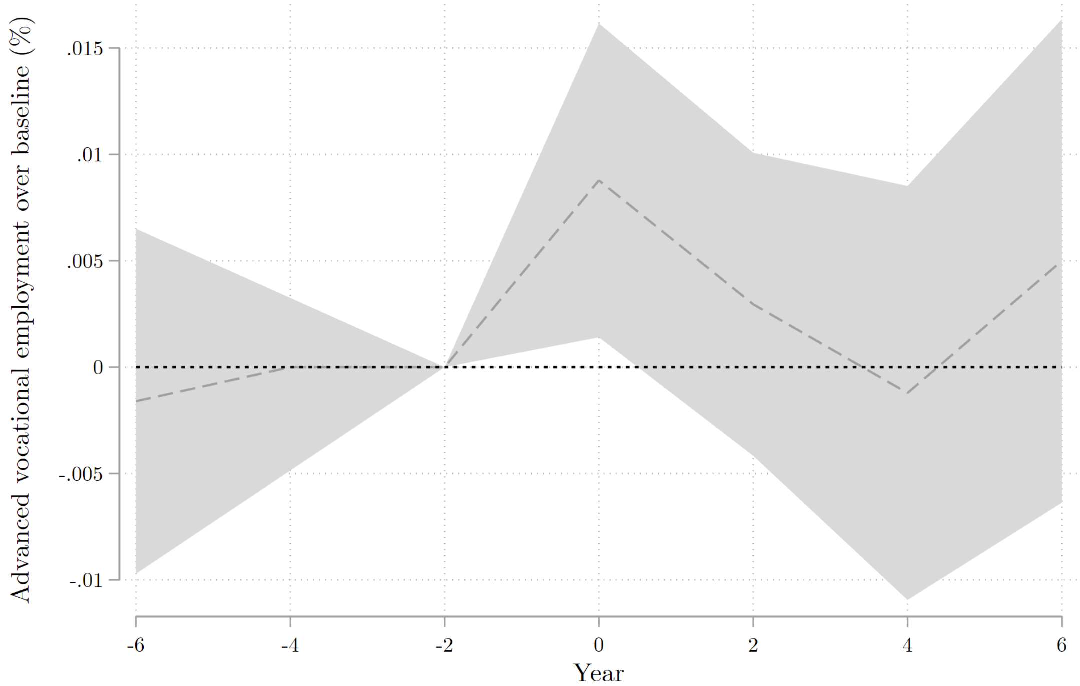
While among Europe's top innovators, the countries considered are quite different in terms of their labour market institutions and local and regional systems of innovation. Therefore, the following presents estimation results by country. The effects follow broadly the same trends across countries, but with variation in the magnitude of effects. As the sample sizes are smaller when estimating by country, it is to be expected that confidence intervals become larger and some effects are statistically insignificant as a result.

Figure 4.8: Advanced vocational employment response to graduate employment shock



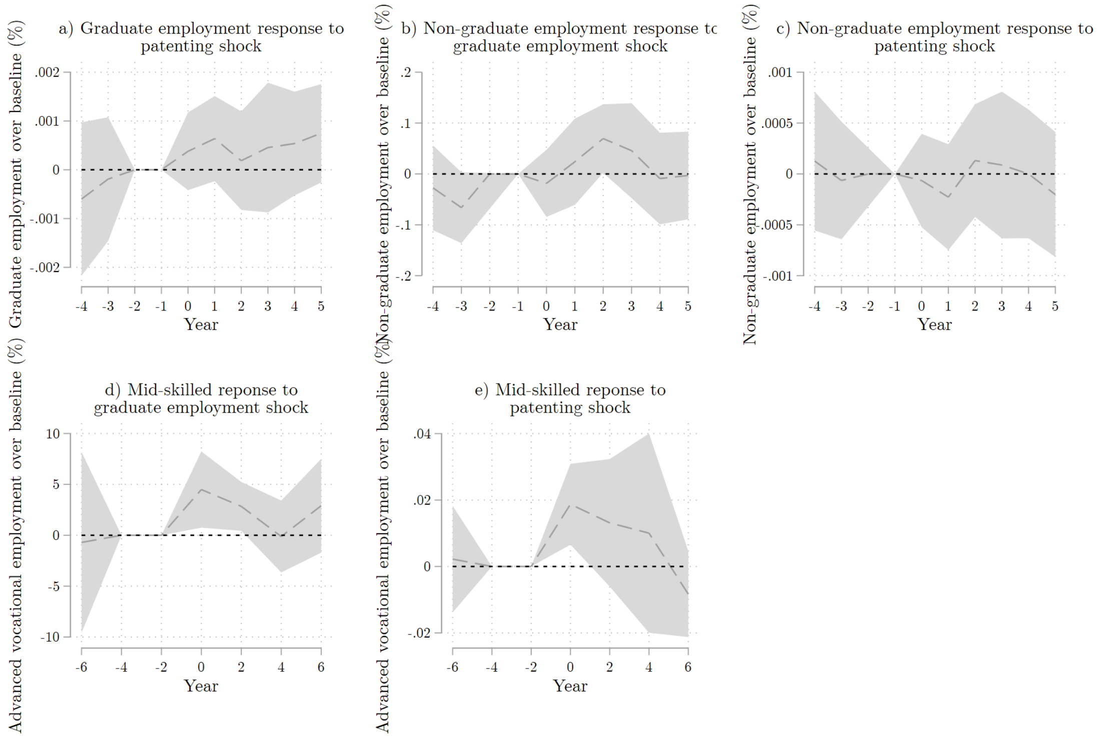
Note: Plot of β_h^ps from equation 4.4 against time horizon h. Baseline in t-2. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in table 4.A.4.

Figure 4.9: Advanced vocational employment response to patenting shock



Note: Plot of β_h^ps from equation 4.4 against time horizon h. Baseline in t-2. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in table 4.A.4.

Figure 4.10: Estimations for France

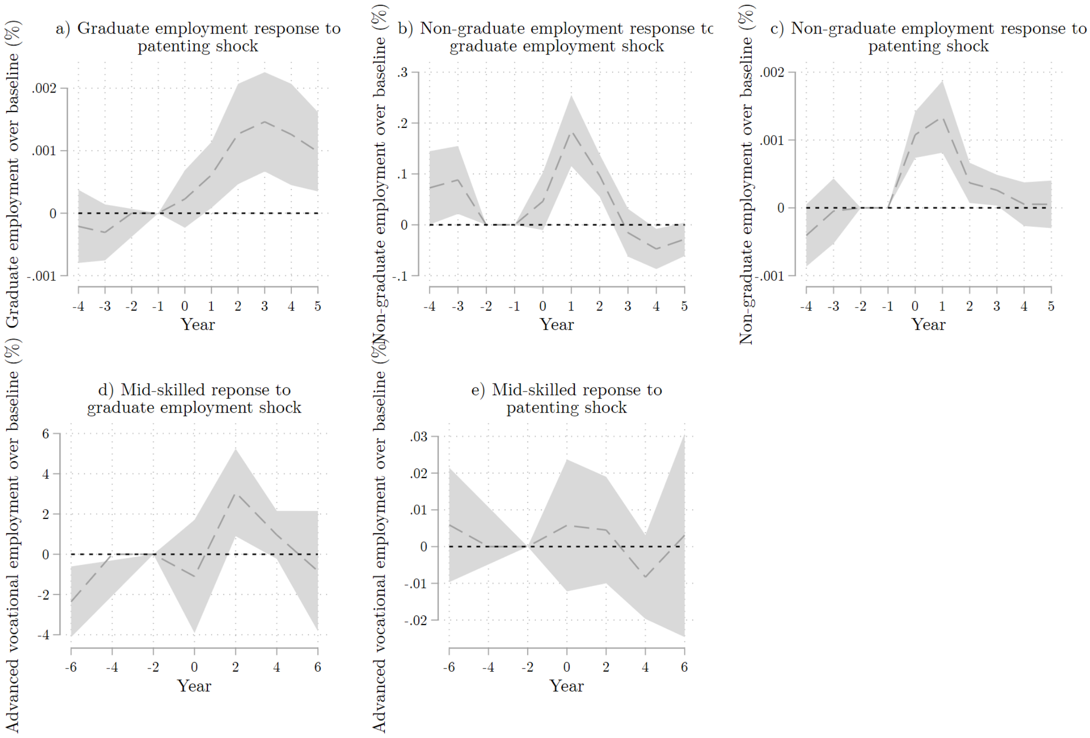


Note: Plot of β coefficients from equations 4.2-4.4 including French regions only. Baseline in t-1 for figure a)-c) and in t-2 for d) and e). 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in tables 4.A.5 - 4.A.7.

The estimates for France in figure 4.10 are broadly similar to the pooled estimates. However, the effect of patenting on graduate employment is statistically insignificant despite point estimates that show a similar pattern and are larger in magnitude than in the whole sample. While there is a small, marginally significant effect of graduate employment on non-graduate employment, the effect of patenting on non-graduate employment hovers around zero.

Figure 4.11 shows results for Germany. The effect of patenting on graduate employment is statistically significant and larger in magnitude than in the overall sample. There is a large positive effect from graduate employment on non-graduate employment. Like in the full sample, this disappears again by year 3. However, there is also a significant positive effect before year -2, suggesting that the effect may be driven by an unobserved variable that affects both graduate and non-graduate employment. The effect of graduate employment on mid-skilled workers is larger in magnitude than that for all non-graduates,

Figure 4.11: Estimations for Germany



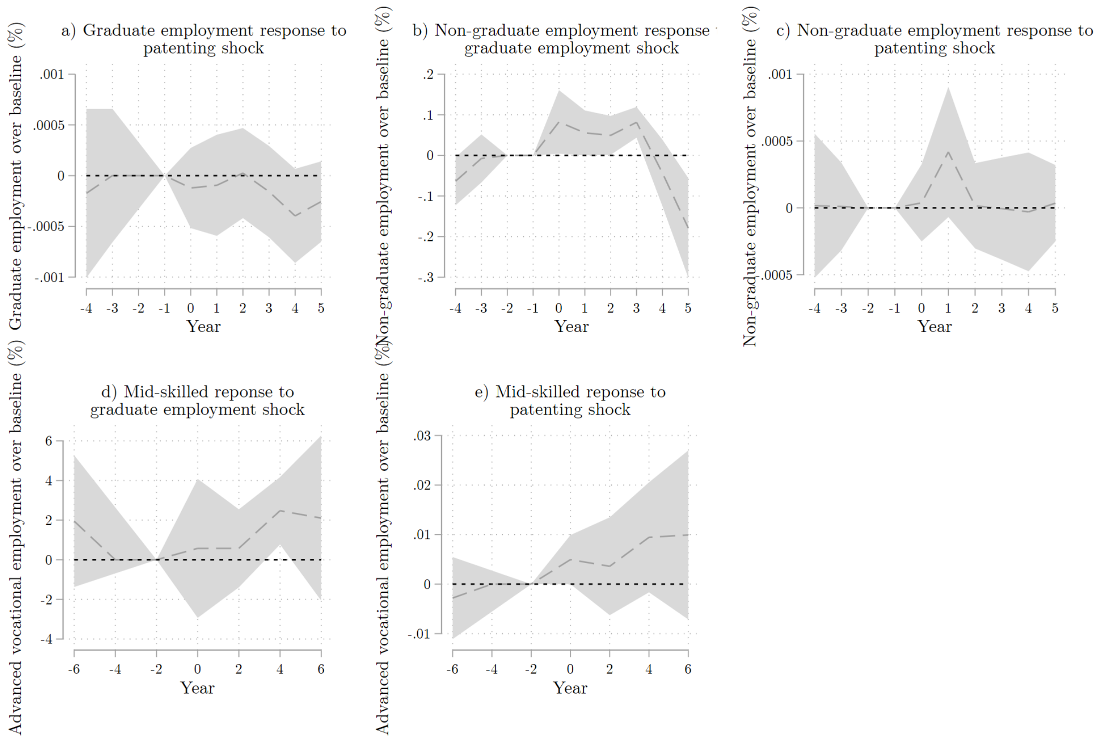
Note: Plot of β coefficients from equations 4.2-4.4 including German regions only. Baseline in t-1 for figure a)-c) and in t-2 for d) and e). 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in tables 4.A.5 - 4.A.7.

but only statistically significant in year 2. In contrast, there is no significant effect of patenting on mid-skilled employment.

Figure 4.12 shows the estimates for the UK. Given the relatively low levels of patenting in most regions in the UK, it is unsurprising to find no significant effect from patenting in panels a), c), and e). However, the effects from graduate employment on non-graduate and mid-skilled employment are also small and short-lived. In the case of mid-skilled employment, this is somewhat to be expected, as the UK system of vocational training is relatively weak compared to France and Germany. The small response from non-graduate employment is surprising given the UKs flexible labour market regime.

The results are suggestive of differences in the effects across the three countries. Some of these differences can be rationalised given what we know about the countries innovation and education systems, as well as industry specialisations. For example, it may be expected that the response of non-graduate employment to a patenting shock is larger in Germany, if

Figure 4.12: Estimations for the UK



Note: Plot of β coefficients from equations 4.2-4.4 including UK regions only. Baseline in t-1 for figure a)-c) and in t-2 for d) and e). 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in tables 4.A.5 - 4.A.7.

a successful invention can be commercialised, leading to increased production in the large domestic manufacturing sector. However, it is surprising that this effect is not mirrored in the response of mid-skilled employment, suggesting further research into the adjustment channels is required.

4.4.5 Job-year multiplier calculation

In keeping with the literature, I calculate jobs multipliers from the coefficients estimated above (Moretti & Thulin, 2013; Lee & Clarke, 2019). To calculate impacts in terms of jobs created, the β_h coefficients, which can be interpreted as elasticities, are multiplied by the ratio of dependent to explanatory variable (Van Dijk, 2018). The multiplier for the effect of graduate employment on non-graduate employment is provided by equation 4.5, where $\overline{emp^{ng}}$ is average non-graduate employment and $\overline{emp^{g}}$ is average graduate employment per region and year in the estimation sample. Note that this is not the number of new jobs, but additional job-years over the estimation horizon between t and t+6. This calculation is more appropriate than a calculation of the number of jobs created, as some of the effects take time to materialise while others are only temporary and decline over time. A multiplier calculated for one point in time cannot reflect these dynamics.

$$M^{g,ng} = \sum_{i=1}^{h} \beta_h * \frac{\overline{EMP^{ng}}}{\overline{EMP^{g}}} \tag{4.5}$$

For the patenting coefficients, the calculation is slightly different, because patenting is measured as patents filed per year in logs. The coefficient is approximately equal to the predicted change in the employment growth rate, but needs to be divided by 100, as equation 4.6 shows.

$$M^{pat,ng} = \sum_{i=1}^{h} \frac{\beta_h}{100} * \frac{\overline{EMP^{ng}}}{\overline{PAT}} \tag{4.6}$$

Multiplier estimates for the whole sample as well as by country are provided in table 4.3. Because they are derived from different regressions for each estimation horizon, it is not possible to derive standard errors for the combined effects. Note that some of these effects are derived from statistically insignificant results.

Across the three countries, a patent is estimated to create 2.2 graduate job-years, e.g. 2.2 jobs for one year, or 1.1 jobs that remain for two years. Across NUTS2 regions, an average of 472 patents are filed per year. By a back-of-the-envelope calculation, patenting can account for 208 additional jobs, or 0.07% of total graduate employment[1]. While this overall effect is small, there is substantial variation across countries. The effect of graduate jobs per patent is largest in Germany, at 1.78 job-years per patent. This translates into 259 additional graduate jobs on average per year and NUTS2 region, representing 0.1% of total graduate employment. The effect in France is slightly smaller, at 1.6 job-years (150 job-years or 0.04% total graduate employment). The estimate for the UK is negative, at 1.47. However, all underlying point estimates are statistically insignificant, implying that the effect is overall close to zero.

Table 4.3: Job-year multipliers

	All	France	Germany	UK
Graduate job-years per patent	2.20	1.60	1.78	-1.47
Non-graduate job-years per graduate job	0.35	0.034	1.09	-0.046
Non-graduate job-years per patent	0.90	-0.35	2.49	1.21
Higher vocational job-years per graduate job	2.42	3.84	-0.19	3.13
Higher vocational job-years per patent	5.62	14.2	3.54	18.2

Note: Multipliers derived from beta coefficients depicted in figures 4.4 to 4.12. Multipliers can be interpreted as additional job-years created due to an additional job/ patent over a five year horizon.

Looking at the effects for non-graduate jobs, the overall multiplier is 0.35 job-years per graduate job for the whole sample. This is an economically meaningful number, corresponding to 22,000 jobs on average per year and NUTS2 region, or 5% of total non-graduate employment. By country, the effect is largest in Germany at 1.09 job-years per graduate job (60,386 jobs per NUTS2 region, or a share of 8%). The effects for France and the UK are close to zero, corresponding to insignificant point estimates throughout. These estimates are comparable to those found in the literature. Lee and Clarke (2019) estimate the effect for a single point in time over a 6-year period. However, the employment groups considered are different, as they consider the effect of high-tech on non-tradable employment. Their preferred specification yields a multiplier of 0.6. For comparison, the

[1]This is calculated as job-year multiplier divided by 5 to annualise the effect, and multiply by the average number of patents per year and region.

estimates in 4.3 should be divided by 5 to arrive at an annualised effect. They are therefore considerably smaller than Lee and Clarke (2019)'s effects, ranging from 0.0028 for Germany to 0.122 for the combined sample. The latter effect is similar to OLS estimates by Lee and Clarke (2019). Moretti and Thulin (2013) consider 10-year intervals for the United States and 6-year intervals for Sweden for the effect of tradable on non-tradable employment. Their preferred estimates for the effects of tradable employment on non-tradable unskilled are 0.3 for the United States and between -0.27 and 0.51 for Sweden. This last estimate is most similar to estimates arrived at here. It should be noted though that the tradable jobs are a smaller subset of overall employment than graduate employment. It is therefore not surprising that the magnitudes of effects are somewhat different.

The patent multiplier for non-graduates is smaller than that for graduates, at 0.9 job-years per patent, corresponding to the small and partly insignificant point estimates seen in figure 4.7. This corresponds to 85 jobs on average per NUTS2 region, or 0.01% of non-graduate employment. The effects from patenting on non-graduates is largest in Germany, at 2.49 job years per patent (363 jobs per NUTS2 region, or 0.05% of total non-graduate employment), derived from point estimates that are statistically significant from year 0 to 3. The estimated multiplier for France is negative but small, at -0.35, and based on overall insignificant point estimates. While the multiplier for the UK is relatively large, at 1.21, this is also based on insignificant point estimates.

The multiplier effects for mid-skilled, or vocational employment are larger in magnitude, in particular the patent multiplier. The overall multiplier predicts 2.42 mid-skilled jobs to be created for every graduate job, corresponding to 376,068 jobs on average per year at the NUTS1 level, or 91% of mid-skilled employment. The patent multiplier is estimated at 5.62 mid-skilled jobs per patent, corresponding to 1226 jobs and 0.05% of total mid-skilled employment.

At the country level, the estimated multipliers are more difficult to interpret, as many of the underlying point estimates are statistically insignificant. This is also driven by small sample sizes, as these estimates rely on a smaller number of regions at a higher level of aggregation, and a shorter time series. For France, both multipliers are based on point estimates that are statistically significant at the beginning of the estimation period but then turn insignificant. The estimates predict 3.84 additional mid-skilled jobs per graduate job (166,800 jobs, 44% of total mid-skilled employment) and 14.2 additional mid-skilled jobs per patent (2,590 jobs, 0.6% of total mid-skilled employment). The estimated multipliers are similar for the UK, at 3.13 mid-skilled jobs per graduate job, and 18.2 mid-skilled jobs per patent. However, the patent multiplier is based on statistically insignificant point estimates throughout. The large magnitude of the multiplier may be explained by overall very low levels of patenting in many regions. The multipliers for mid-skilled employment for Germany are difficult to interpret due to the volatility of the underlying point estimates. The graduate employment multiplier is small and negative, but this masks significant positive point estimates in the middle of the estimation period, while those at the beginning and end are negative but statistically insignificant. Similarly, the point estimates for the patent multiplier hover around zero.

4.5.Discussion and conclusion

The empirical results provide evidence for the model outlined in section 4.2.3. While much of the literature has focused on the effect of invention and innovation on graduate or high-skilled employment, as well as the effect of graduates on non-graduates, there is also a limited effect on those with vocational qualifications and those without university degrees. Furthermore, the results are suggestive of the intermediating role played by the wider institutional environment, including national and regional systems of innovation and education.

The results confirm a significant multiplier effect from graduate on non-graduate employment. While the effect is only temporary, there is also a significant positive effect of patenting on non-graduate employment. The local projections method shows that considering these effects over several years, instead of a single point in time is important. The effects of patenting on graduate employment, and the effect of graduate on non-graduate employment and mid-skilled employment rise over two to three years and then decline again. In contrast, the effects of patenting on non-graduate and mid-skilled employment are relatively short lived, and employment reverts back to the baseline after a short, positive impact.

The positive effect of patenting on non-graduate employment, even if short-lived, shows that not all innovation may be labour-displacing at the regional level. As expected, the magnitude of the effect is larger for workers with advanced vocational qualifications that may themselves contribute to the innovation process (Filippetti & Guy, 2016). This suggests that innovative firms and industries may to some extend halt or slow down the decline in employment of some mid-skilled occupations. However, these jobs are likely to be different from jobs consisting predominantly of routine tasks that are declining fastest, instead requiring creativity and soft skills (Aghion et al., 2019; Filippetti & Guy, 2020).

This warrants further research into the adjustment channels. First, who are the people taking the additional jobs? Additional jobs may be filled by transition from unemployed or inactivity, or by internal or international migrants. Research by Bartik (1993) on the effects of local economic policy suggests that the latter effect is important as an adjustment mechanism. This may be particularly the case in countries like the UK, where unemployment is generally low. However, it is possible that the creation of new jobs allows locals to climb the job ladder. With the available data, it is only possible to see absolute changes in employment, without an indication of churn within local labour markets. This leads to the second question, regarding where jobs are being created, as well as their quality. Both graduate and non-graduate jobs may be created at the innovating businesses or in the wider economy. A successfully innovating firm may hire more scientists and engineers to invest in further innovation. They might also require additional skills in marketing and distribution, if the invention processes through to commercialisation. They might also requiring additional workers in manufacturing or installation. On the other hand, jobs may be created in local services, both high- and low-skilled, which may or may not be related to the initial shock. Third, it would be expected that these adjustment mechanisms vary significantly by industry, occupation and technology class. Some industries exhibit stronger complementarities between skilled and unskilled labour than others. Additionally, while some technologies are complementary to labour, others are labour substituting. An incremental innovation may increase a firm's competitive advantage, making its workers more productive and ultimately lead to more employment as the firm expands. Disruptive new technologies may displace older firms and industries, also making skills required previously obsolete.

Answering these questions requires situating technological invention in the wider innovation process. Invention is just the first stage in a longer innovation process that leads to commercialisation, and may also involve process and product innovation. Differentiating useful inventions from those that do not lead to any further innovation would make the estimates presented more precise. Furthermore, information about the following steps yields insights into the effects expected. Commercialisation often takes places at a different location from the initial invention (Feldman, 1994). Many inventions, particularly by specialised research labs or universities are also licensed rather than commercialised in-house. The time frames of this process also depend on the technology and industry in question. While some jobs will be created throughout the innovation process, others will follow from commercialisation.

There is significant heterogeneity across the three countries studied. For France, there are no significant effects on non-graduates of either graduate employment or patenting. This suggests that rigid labour protection legislation may may prevent labour markets from adjusting (Griffith & Macartney, 2014). However, there are significant effects for those with vocational qualifications. These qualifications may make it easier to demonstrate their skills to hiring firms, in turn lowering their risk in the face of strict employment protection. Interestingly, the opposite is observed in Germany. While non-graduate employment shows a strong, significant reaction to shocks in graduate employment and patenting, the effect of graduate employment on mid-skilled employment is statistically significant only for one year, and the effect of patenting is insignificant throughout. A possible explanation is that, while employment protection and unemployment insurance for relatively low-skilled and low-paid jobs have been reduced, those with vocational education, especially in the highly innovative manufacturing industries, still enjoy relatively high levels of protection, also due to the stronger role of unions and works councils.

Further research can unpack these differences, in particular by comparing a wider set of countries, or by studying the effects of institutional arrangements over time. More liberal labour market regimes, such as in the UK, may be more conducive to radical innovation, while at the same time allowing for swifter labour market adjustment (Akkermans, Castaldi, & Los, 2009; Griffith & Macartney, 2014). This should also consider any differences in the quality of jobs that are created by different innovations, as Kemeny and Osman (2018) and Lee and Clarke (2019) find that jobs created through the multiplier effect from high-tech employment may have an overall negative effect on average earnings in liberal labour market regimes such as in the US and the UK. In relatively inflexible labour markets such as the French, incentives may be higher to invest in labour-substituting innovation. While labour displacing technology is often feared (Caselli & Manning, 2017), the countries studied also suffer from skills shortages in the face of changing technology. Further research into the adjustment channels can reveal whether some labour market institutions are more conducive to making use of technological opportunities, not only by providing a flexible labour force, but also incentivising investments in the skills required.

Appendix

4.A. Additional tables

Table 4.A.1: Graduate employment response to patenting shock

	t-4	t-3	t	t+1	t+2	t+3	t+4	t+5
L.Log patents	0.0049	0.015	0.039**	0.069***	0.077***	0.079***	0.054**	0.048**
	(0.023)	(0.019)	(0.016)	(0.020)	(0.019)	(0.023)	(0.023)	(0.019)
L.Log grad. emp.	-0.69***	-0.87***	-0.34***	-0.56***	-0.65***	-0.67***	-0.68***	-0.73***
	(0.037)	(0.041)	(0.035)	(0.039)	(0.028)	(0.032)	(0.051)	(0.046)
L2.Log grad. emp.	0.34***	0.64***	0.14***	0.28***	0.27***	0.22***	0.20***	0.23***
	(0.039)	(0.034)	(0.036)	(0.037)	(0.046)	(0.036)	(0.036)	(0.035)
Log pop density	1.49***	0.89***	0.33*	0.54**	1.11***	1.43***	1.59***	1.64***
	(0.22)	(0.14)	(0.18)	(0.25)	(0.25)	(0.24)	(0.24)	(0.23)
Recession (2009-2010)	0.0048	-0.0021	0.016***	0.017**	0.027***	0.035***	0.013**	-0.0043
	(0.0057)	(0.0054)	(0.0047)	(0.0068)	(0.0062)	(0.0062)	(0.0052)	(0.0054)
Constant	-6.26***	-3.69***	-0.86	-1.74	-4.29***	-5.59***	-6.17***	-6.27***
	(1.12)	(0.71)	(0.88)	(1.26)	(1.22)	(1.16)	(1.16)	(1.11)
Observations	892	892	892	892	892	892	892	892
within R^2	0.33	0.44	0.15	0.25	0.35	0.42	0.44	0.51
between R^2	0.0063	0.0069	0.0014	0.0037	0.0024	0.0041	0.013	0.018
overall R^2	0.0028	0.0043	0.0027	0.0044	0.0032	0.0043	0.0094	0.015
F-statistic	80.1	115.4	27.6	42.3	127.3	98.2	38.5	56.4
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

* p <0.1, ** p <0.05, *** p <0.01.

Note: The top row shows the estimation horizon. The dependent variable is graduate employment growth over the estimation horizon, e.g. between t-4 and t-1 in the first column and between t+5 and t-1 in the last column. t-1 and t-2 not estimated due to multicollinearity. Estimation at the NUTS2 region level. Region fixed effects included in all specifications.

Table 4.A.2: Patenting response to graduate employment shock

	t-4	t-3	t-2	t	t+1	t+2	t+3	t+4	t+5
L.Log patents	0.21***	0.35***	0.39***	0.34***	0.28***	0.16***	0.16***	0.12**	0.051
	(0.073)	(0.044)	(0.058)	(0.057)	(0.049)	(0.051)	(0.051)	(0.048)	(0.043)
L.Log grad. emp.	0.44***	0.27***	0.23***	0.058	0.0073	0.017	-0.064	0.019	0.063
	(0.067)	(0.047)	(0.046)	(0.047)	(0.066)	(0.060)	(0.059)	(0.069)	(0.066)
Log pop density	-0.92*	-0.92**	-0.68*	-0.031	0.33	0.76*	1.17***	0.91**	0.58
	(0.55)	(0.44)	(0.37)	(0.37)	(0.37)	(0.41)	(0.42)	(0.41)	(0.41)
Recession (2009-2010)	0.054***	0.083***	0.044***	-0.0060	0.0098	-0.0077	0.0014	0.020	0.017
	(0.011)	(0.013)	(0.012)	(0.0088)	(0.010)	(0.010)	(0.011)	(0.013)	(0.012)
Constant	6.95**	7.12***	5.84***	3.60*	2.27	0.56	-1.23	0.0091	1.89
	(2.91)	(2.43)	(2.04)	(2.01)	(2.01)	(2.24)	(2.27)	(2.21)	(2.17)
Observations	892	892	892	892	892	892	892	892	892
within R^2	0.20	0.25	0.23	0.14	0.095	0.045	0.048	0.042	0.025
between R^2	0.012	0.034	0.16	0.99	0.61	0.25	0.17	0.18	0.18
overall R^2	0.0099	0.031	0.16	0.97	0.61	0.26	0.18	0.19	0.19
F-statistic	20.3	38.8	25.0	11.0	10.1	3.5	4.2	3.5	1.8
P of model test	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.14

* p <0.1, ** p <0.05, *** p <0.01.

Note: The top row shows the estimation horizon. The dependent variable is patenting growth over the estimation horizon, e.g. between t-4 and t-1 in the first column and between t+5 and t-1 in the last column. t-1 not estimated due to multicollinearity. Estimation at the NUTS2 region level. Region fixed effects included in all specifications.

Table 4.A.3: Non-graduate employment response to employment and patenting shocks

	t-4	t-3	t-2	t	t+1	t+2	t+3	t+4
L.Log patents	0.024	0.016	0.028***	0.050***	-0.0027	-0.017	-0.020	-0.011
	(0.018)	(0.012)	(0.0098)	(0.016)	(0.011)	(0.011)	(0.012)	(0.013)
L. Δ log grad. emp.	-0.033	-0.0055	0.049**	0.083***	0.073***	0.066***	-0.014	-0.068**
	(0.022)	(0.019)	(0.021)	(0.025)	(0.019)	(0.020)	(0.023)	(0.034)
L.Log non-grad emp.	-1.18***	-1.14***	-0.44***	-0.78***	-0.97***	-0.95***	-1.12***	-1.11***
	(0.032)	(0.034)	(0.044)	(0.049)	(0.060)	(0.033)	(0.050)	(0.052)
L2.Log non-grad emp.	0.27***	0.58***	-0.11***	-0.19***	-0.10**	-0.12***	0.014	0.073
	(0.044)	(0.039)	(0.035)	(0.038)	(0.044)	(0.037)	(0.041)	(0.057)
Log pop density	0.68***	0.31**	-0.58***	-1.14***	-1.27***	-1.22***	-1.21***	-1.09***
	(0.18)	(0.13)	(0.073)	(0.13)	(0.15)	(0.14)	(0.14)	(0.14)
Recession (2009-2010)	0.029***	0.020***	-0.011***	-0.0061	-0.012***	-0.019***	-0.014***	-0.0045
	(0.0043)	(0.0023)	(0.0028)	(0.0044)	(0.0039)	(0.0037)	(0.0040)	(0.0042)
Constant	1.95*	1.78**	6.44***	12.0***	13.7***	13.5***	13.7***	12.6***
	(1.01)	(0.70)	(0.50)	(0.76)	(0.80)	(0.79)	(0.81)	(0.73)
Observations	892	892	892	892	892	892	892	892
within R^2	0.55	0.57	0.34	0.60	0.70	0.71	0.70	0.66
between R^2	0.0075	0.0069	0.0070	0.062	0.050	0.046	0.047	0.053
overall R^2	0.0041	0.011	0.00010	0.0024	0.0056	0.0094	0.013	0.020
F-statistic	340.4	284.9	96.6	116.9	209.5	349.1	143.1	169.4
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

* p <0.1, ** p <0.05, *** p <0.01.

Note: The top row shows the estimation horizon. The dependent variable is non-graduate employment growth over the estimation horizon, e.g. between t-4 and t-1 in the first column and between t+5 and t-1 in the last column. t-1 not estimated due to multicollinearity. Estimation at the NUTS2 region level. Region fixed effects included in all specifications.

Table 4.A.4: Advanced vocational employment response to employment and patenting shocks

	t-6	t	t+2	t+4	t+6
L.Log patents 2y.	-0.16	0.88**	0.30	-0.12	0.50
	(0.41)	(0.37)	(0.36)	(0.49)	(0.57)
L2. Δ log grad. emp.	-1.23	0.90	2.53***	1.37**	1.02
	(1.09)	(1.15)	(0.72)	(0.64)	(0.93)
L2. Δ log mid-skilled emp	-0.47***	-0.48***	-0.48***	-0.52***	-0.43***
	(0.078)	(0.056)	(0.059)	(0.049)	(0.066)
Log pop density	1.62	1.18	2.22	4.52*	4.09
	(1.92)	(0.94)	(1.58)	(2.68)	(2.92)
Recession (2009-2010)	0.093	0.20*	0.057	0.0036	0.014
	(0.15)	(0.11)	(0.11)	(0.088)	(0.086)
Constant	-8.01	-12.8**	-14.3*	-24.2	-26.3
	(11.3)	(4.74)	(8.47)	(14.6)	(16.4)
Observations	209	249	209	169	131
within R^2	0.21	0.29	0.40	0.48	0.37
between R^2	0.019	0.027	0.036	0.024	0.0057
overall R^2	0.0094	0.010	0.0098	0.00081	0.000092
F-statistic	11.7	21.0	36.8	31.3	11.8
P of model test	0.00	0.00	0.00	0.00	0.00

* p <0.1, ** p <0.05, *** p <0.01.

Note: The top row shows the estimation horizon. Consistent with data availability, the estimation horizon increases in steps of two years. The dependent variable is advanced vocational employment growth over the estimation horizon, e.g. between t-6 and t-2 in the first column and between t+6 and t-2 in the last column. t-2 and t-4 not estimated due to multicollinearity. Vocational employment is normalised by total employment. Log patent applications include all applications in last two years. Estimation at the NUTS1 region level. Region fixed effects included in all specifications.

Table 4.A.5: Graduate employment response to patenting shocks by country

	t-4	t-3	t-2	t	t+1	t+2	t+3	t+4
France								
L.Log patents	-0.060	-0.019	0.038	0.064	0.019	0.046	0.054	0.075
	(0.079)	(0.064)	(0.040)	(0.044)	(0.051)	(0.067)	(0.054)	(0.051)
L.Log grad. emp.	-0.80***	-0.98***	-0.42***	-0.74***	-0.80***	-0.83***	-0.82***	-0.88***
	(0.074)	(0.074)	(0.083)	(0.069)	(0.062)	(0.080)	(0.11)	(0.087)
L2.Log grad. emp.	0.37***	0.68***	0.021	0.16**	0.14*	0.15**	0.11	0.098
	(0.098)	(0.071)	(0.065)	(0.068)	(0.071)	(0.065)	(0.070)	(0.064)
Log pop density	3.29***	2.12***	1.82***	2.71***	3.37***	3.27***	3.21***	3.21***
	(0.84)	(0.48)	(0.64)	(0.75)	(0.73)	(0.70)	(0.58)	(0.54)
Constant	-12.6***	-8.10***	-6.40**	-9.65***	-11.9***	-11.5***	-11.1***	-10.7***
	(3.14)	(1.78)	(2.67)	(3.11)	(2.88)	(2.74)	(2.35)	(2.24)
Observations	210	210	210	210	210	210	210	210
within R^2	0.32	0.46	0.22	0.37	0.48	0.52	0.54	0.60
between R^2	0.078	0.055	0.14	0.14	0.12	0.11	0.097	0.086
overall R^2	0.0091	0.0065	0.0015	0.0024	0.0050	0.0075	0.0087	0.0087
F-statistic	43.4	50.6	19.3	38.9	59.3	31.0	17.1	31.7
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Germany								
L.Log patents	-0.021	-0.031	0.023	0.061**	0.13***	0.15***	0.13***	0.098***
	(0.030)	(0.023)	(0.023)	(0.027)	(0.040)	(0.040)	(0.041)	(0.032)
L.Log grad. emp.	-0.68***	-0.81***	-0.29***	-0.40***	-0.63***	-0.50***	-0.59***	-0.74***
	(0.063)	(0.068)	(0.045)	(0.047)	(0.048)	(0.047)	(0.039)	(0.053)
L2.Log grad. emp.	0.26***	0.56***	0.15***	0.21***	0.32***	0.086	0.091	0.24***
	(0.069)	(0.069)	(0.056)	(0.053)	(0.068)	(0.073)	(0.067)	(0.056)
Log pop density	0.31	-0.039	-0.69***	-0.72***	-0.075	0.49	0.48	0.61*
	(0.28)	(0.19)	(0.16)	(0.26)	(0.29)	(0.36)	(0.36)	(0.32)
Constant	0.57	1.72	4.47***	4.72***	1.41	-1.31	-0.68	-1.17
	(1.63)	(1.14)	(1.00)	(1.57)	(1.79)	(2.19)	(2.17)	(1.89)
Observations	354	354	354	354	354	354	354	354
within R^2	0.47	0.48	0.14	0.19	0.31	0.36	0.44	0.56
between R^2	0.12	0.00015	0.037	0.010	0.17	0.20	0.25	0.22
overall R^2	0.0029	0.023	0.0034	0.0015	0.093	0.12	0.18	0.19
F-statistic	41.9	62.7	18.4	20.8	67.8	57.1	70.7	54.3
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UK								
L.Log patents	-0.017	0.00013	-0.012	-0.0095	0.0026	-0.016	-0.040*	-0.026
	(0.042)	(0.033)	(0.020)	(0.025)	(0.022)	(0.023)	(0.023)	(0.020)
L.Log grad. emp.	-0.80***	-1.03***	-0.61***	-0.94***	-0.89***	-0.96***	-0.96***	-0.92***
	(0.10)	(0.088)	(0.063)	(0.069)	(0.064)	(0.073)	(0.12)	(0.099)
L2.Log grad. emp.	0.19**	0.51***	0.011	0.14*	0.11	0.14*	0.13**	0.16***
	(0.071)	(0.052)	(0.061)	(0.074)	(0.089)	(0.075)	(0.060)	(0.051)
Log pop density	2.86***	2.48***	2.93***	3.90***	4.00***	4.10***	4.04***	3.50***
	(0.70)	(0.48)	(0.31)	(0.53)	(0.61)	(0.66)	(0.62)	(0.35)
Constant	-13.2***	-11.5***	-13.5***	-18.0***	-18.7***	-18.9***	-18.4***	-15.7***
	(3.35)	(2.32)	(1.49)	(2.66)	(2.97)	(3.08)	(2.81)	(1.66)
Observations	328	328	328	328	328	328	328	328
within R^2	0.32	0.49	0.35	0.52	0.55	0.61	0.61	0.57
between R^2	0.0018	0.027	0.0066	0.0061	0.020	0.065	0.15	0.17
overall R^2	0.00065	0.0021	0.00035	0.0028	0.0048	0.0088	0.020	0.031
F-statistic	30.5	45.0	35.4	46.4	50.1	84.7	19.8	35.1
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

* p <0.1, ** p <0.05, *** p <0.01.

Note: The top row shows the estimation horizon. The dependent variable is graduate employment growth over the estimation horizon, e.g. between t-4 and t-1 in the first column and between t+5 and t-1 in the last column. t-1 and t-2 not estimated due to multicollinearity. Estimation at the NUTS2 region level. Region fixed effects included in all specifications.

Table 4.A.6: Effects on non-graduate employment by country

	t-4	t-3	t-2	t	t+1	t+2	t+3	t+4
France								
L.Log patents	0.013	-0.0064	-0.0065	-0.023	0.013	0.0088	0.000038	-0.020
	(0.034)	(0.029)	(0.023)	(0.026)	(0.028)	(0.036)	(0.032)	(0.031)
L. Δ log grad. emp.	-0.027	-0.066*	-0.019	0.024	0.070*	0.046	-0.0090	-0.0029
	(0.042)	(0.035)	(0.033)	(0.043)	(0.034)	(0.047)	(0.045)	(0.044)
L.Log non-grad emp.	-1.18***	-1.22***	-0.52***	-0.70***	-0.78***	-0.61***	-0.59***	-0.72***
	(0.070)	(0.078)	(0.087)	(0.099)	(0.088)	(0.084)	(0.083)	(0.100)
L2.Log non-grad emp.	0.14	0.56***	-0.079	0.029	0.20**	0.15*	0.0037	-0.029
	(0.098)	(0.071)	(0.082)	(0.088)	(0.075)	(0.076)	(0.095)	(0.094)
Log pop density	1.10**	0.51**	-0.52*	-0.85***	-1.55***	-1.85***	-1.99***	-1.83***
	(0.40)	(0.23)	(0.25)	(0.28)	(0.31)	(0.32)	(0.38)	(0.40)
Constant	1.65	2.02*	6.38***	8.45***	10.9***	11.6***	13.0***	13.4***
	(1.85)	(1.08)	(1.44)	(1.33)	(1.34)	(1.43)	(1.97)	(2.17)
Observations	210	210	210	210	210	210	210	210
within R^2	0.58	0.60	0.33	0.38	0.45	0.46	0.49	0.51
between R^2	0.21	0.12	0.012	0.049	0.034	0.030	0.018	0.011
overall R^2	0.042	0.044	0.00000021	0.0014	0.0017	0.0025	0.0017	0.00086
F-statistic	85.1	66.5	16.0	19.3	39.9	43.1	20.8	16.6
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Germany								
L.Log patents	-0.041*	-0.0047	0.11***	0.13***	0.037**	0.026**	0.0054	0.0052
	(0.023)	(0.024)	(0.017)	(0.027)	(0.015)	(0.011)	(0.016)	(0.018)
L. Δ log grad. emp.	0.073*	0.088**	0.046	0.19***	0.097***	-0.015	-0.047**	-0.028*
	(0.036)	(0.034)	(0.029)	(0.035)	(0.021)	(0.024)	(0.020)	(0.017)
L.Log non-grad emp.	-1.10***	-1.22***	-0.30***	-0.71***	-1.00***	-1.25***	-1.22***	-1.03***
	(0.063)	(0.052)	(0.049)	(0.043)	(0.034)	(0.044)	(0.045)	(0.042)
L2.Log non-grad emp.	0.21***	0.68***	-0.27***	-0.32***	-0.22***	0.066*	0.24***	0.27***
	(0.054)	(0.051)	(0.049)	(0.038)	(0.034)	(0.034)	(0.030)	(0.029)
Log pop density	-1.35***	-0.82***	-0.097	-0.047	-0.30**	-0.31*	-0.35	-0.42*
	(0.19)	(0.11)	(0.095)	(0.11)	(0.12)	(0.18)	(0.22)	(0.25)
Constant	13.6***	8.08***	3.58***	6.13***	9.38***	9.25***	8.29***	7.28***
	(1.19)	(0.74)	(0.66)	(0.79)	(0.77)	(1.06)	(1.25)	(1.40)
Observations	354	354	354	354	354	354	354	354
within R^2	0.54	0.63	0.36	0.63	0.84	0.86	0.78	0.69
between R^2	0.028	0.020	0.0031	0.050	0.0000012	0.0075	0.016	0.0098
overall R^2	0.00021	0.000056	0.0034	0.0026	0.0023	0.0033	0.0043	0.0021
F-statistic	110.3	215.0	53.3	104.9	262.1	232.0	178.2	171.7
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UK								
L.Log patents	0.0016	0.0011	0.0038	0.042*	0.0016	-0.00057	-0.0030	0.0035
	(0.027)	(0.016)	(0.015)	(0.025)	(0.016)	(0.019)	(0.022)	(0.014)
L. Δ log grad. emp.	-0.064**	-0.0074	0.082**	0.055*	0.049**	0.082***	-0.043	-0.18***
	(0.030)	(0.030)	(0.040)	(0.028)	(0.024)	(0.019)	(0.041)	(0.062)
L.Log non-grad emp.	-1.12***	-1.02***	-0.52***	-0.87***	-1.04***	-0.96***	-1.29***	-1.33***
	(0.041)	(0.035)	(0.059)	(0.058)	(0.092)	(0.040)	(0.061)	(0.053)
L2.Log non-grad emp.	0.19**	0.43***	-0.024	-0.099*	-0.048	-0.28***	-0.11	-0.034
	(0.074)	(0.048)	(0.049)	(0.056)	(0.060)	(0.042)	(0.066)	(0.097)
Log pop density	1.90***	1.20***	-0.91***	-1.80***	-1.92***	-1.52***	-1.26***	-0.85***
	(0.18)	(0.12)	(0.090)	(0.16)	(0.17)	(0.16)	(0.19)	(0.21)
Constant	-5.23***	-3.31***	8.57***	16.0***	17.6***	16.3***	15.7***	13.1***
	(0.98)	(0.68)	(0.53)	(0.86)	(1.04)	(0.98)	(1.16)	(0.94)
Observations	328	328	328	328	328	328	328	328
within R^2	0.70	0.62	0.41	0.76	0.79	0.81	0.82	0.80
between R^2	0.0013	0.0094	0.0016	0.037	0.029	0.031	0.045	0.072
overall R^2	0.0017	0.0042	0.00067	0.00031	0.00021	0.00031	0.00051	0.0017
F-statistic	325.2	278.9	83.1	114.3	103.9	249.8	397.4	426.9
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: The top row shows the estimation horizon. The dependent variable is non-graduate employment growth over the estimation horizon, e.g. between t-4 and t-1 in the first column and between t+5 and t-1 in the last column. t-1 not estimated due to multicollinearity. Estimation at the NUTS2 region level. Region fixed effects included in all specifications.

Table 4.A.7: Effects on advanced vocational employment by country

	t-6	t	t+2	t+4	t+6
France					
L.Log patents 2y.	0.22	1.87**	1.31	1.00	-0.83
	(0.81)	(0.61)	(0.97)	(1.51)	(0.65)
L2. Δ log grad. emp.	-0.70	4.50**	2.84**	-0.12	2.91
	(4.49)	(1.89)	(1.21)	(1.78)	(2.33)
L2. Δ log mid-skilled emp	-0.67***	-0.62***	-0.66***	-0.70***	-0.62***
	(0.21)	(0.087)	(0.095)	(0.15)	(0.066)
Log pop density	-3.76	4.74	-0.78	3.14	15.0*
	(7.40)	(2.75)	(3.19)	(7.71)	(5.54)
Recession (2009-2010)	0.93*	0.84***	0.56	0.47*	0.43**
	(0.45)	(0.18)	(0.34)	(0.24)	(0.096)
Constant	16.9	-37.3**	-5.92	-23.1	-70.3**
	(37.7)	(12.3)	(10.8)	(30.5)	(23.6)
Observations	44	56	44	32	20
within R^2	0.45	0.60	0.59	0.74	0.84
between R^2	0.18	0.0014	0.18	0.0032	0.10
overall R^2	0.00015	0.0057	0.21	0.0032	0.00048
F-statistic	5.8	21.8	22.9	.	.
P of model test	0.01	0.00	0.00	.	.
Germany					
L.Log patents 2y.	0.59	0.58	0.45	-0.83	0.31
	(0.79)	(0.91)	(0.73)	(0.58)	(1.40)
L2. Δ log grad. emp.	-2.36**	-1.10	3.07**	0.96	-0.84
	(0.89)	(1.42)	(1.10)	(0.60)	(1.51)
L2. Δ log mid-skilled emp	-0.54***	-0.38***	-0.43***	-0.50***	-0.29**
	(0.10)	(0.078)	(0.11)	(0.051)	(0.13)
Log pop density	4.13*	2.91*	7.38***	12.6***	9.52**
	(2.15)	(1.51)	(1.78)	(2.42)	(4.21)
Recession (2009-2010)	0.070	0.22	-0.074	-0.15	-0.027
	(0.18)	(0.15)	(0.18)	(0.12)	(0.16)
Constant	-28.1*	-20.8***	-45.3***	-65.5***	-56.2*
	(14.6)	(6.56)	(10.9)	(14.7)	(28.9)
Observations	93	109	93	77	63
within R^2	0.34	0.21	0.46	0.62	0.27
between R^2	0.030	0.016	0.024	0.017	0.0079
overall R^2	0.013	0.0037	0.00030	0.0071	0.0023
F-statistic	15.2	13.3	90.2	73.3	2.1
P of model test	0.00	0.00	0.00	0.00	0.12
UK					
L.Log patents 2y.	-0.28	0.49*	0.36	0.94	0.99
	(0.42)	(0.25)	(0.50)	(0.56)	(0.86)
L2. Δ log grad. emp.	1.95	0.58	0.58	2.47**	2.10
	(1.68)	(1.77)	(0.99)	(0.86)	(2.10)
L2. Δ log mid-skilled emp	-0.25**	-0.57***	-0.43***	-0.49***	-0.50***
	(0.11)	(0.088)	(0.041)	(0.095)	(0.11)
Log pop density	-1.60	-1.02	-3.55***	-2.75	-2.75
	(2.16)	(1.40)	(1.13)	(1.71)	(2.17)
Recession (2009-2010)	-0.17	-0.014	-0.097	0.12	0.12
	(0.18)	(0.21)	(0.12)	(0.15)	(0.15)
Constant	11.0	2.63	18.3***	9.60	9.38
	(10.5)	(8.34)	(5.12)	(11.1)	(16.3)
Observations	72	84	72	60	48
within R^2	0.16	0.41	0.43	0.52	0.60
between R^2	0.16	0.00000032	0.0069	0.020	0.018
overall R^2	0.0021	0.049	0.0014	0.0020	0.023
F-statistic	4.0	26.1	36.6	24.3	12.5
P of model test	0.03	0.00	0.00	0.00	0.00

* p <0.1, ** p <0.05, *** p <0.01.

Note: The top row shows the estimation horizon. Consistent with data availability, the estimation horizon increases in steps of two years. The dependent variable is advanced vocational employment growth over the estimation horizon, e.g. between t-6 and t-2 in the first column and between t+6 and t-2 in the last column. t-2 and t-4 not estimated due to multicollinearity. Vocational employment is normalised by total employment. Log patent applications include all applications in last two years. Estimation at the NUTS1 region level. Region fixed effects included in all specifications.

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