Empirical Essays in Economic Geography and Labour Economics: Regulations and the Labour Market Consequences of Automation and Innovation

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Declaration

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

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

I declare that my thesis consists of 46443 words.

Statement of co-authored work

I confirm that Chapter 2 was jointly co-authored with Dr. Vassilis Monastiriotis and Professor Neil Lee. I contributed a minimum of 70% of the total work.

Statement of inclusion of previous work

I can confirm that Chapter 5 was inspired by a previous study (for a MSc award) I undertook at the London School of Economics in 2017. The content, methodology and results have been significantly revised.

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Abstract

This thesis is comprised of four distinct, original pieces of research on topics related to economic geography and the labour market consequences of innovation and automation. The first chapter outlines the thesis and sets the scene. The second chapter studies the determinants of the variation in the returns to college education across U.S. cities. We find that local innovation exerts a positive influence on local education returns and such effects are particularly pronounced in larger cities. Our findings have implications for within-city levels of inequality, particularly across the skill distribution. The next two chapters in the thesis relate to the role of automation technologies and their implications for labour markets, specifically concerning the recent arrival and widespread use of industrial robots in the production process. Hence, the third chapter examines the use of robots in the U.K. exploring trends across local labour markets. The study yields interesting findings in employment dynamics across occupations and industries that echo past studies. The fourth chapter assesses the role of the same technology in a cross-country setting with an emphasis on industry linkages. I find that greater rates of robot usage in one industry are positively associated with the labour market outcomes of downstream sectors. This effect is likely driven by price mechanisms when industries experience technological change that raise their productivity potential. The final chapter explores the local growth consequences of land use regulation in U.S. cities. I find that the composition of local growth outcomes can be influenced by the level of regulatory constraints on housing, particularly in high demand localities. I hope the findings and insights from this thesis can have the potential to possibly inform aspects of urban, innovation and/or labour market policies.

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Chapter 1: Introduction

This Ph.D. thesis is comprised of four novel and distinct empirical works in topics in economic geography and labour economics. My thesis is primarily concerned with two main research issues: 1) the spatial, labor market and growth implications of technological change as well as 2) the local growth consequences of land-use regulation. Overarching my research work, is a concern about how supply-side developments arising from technology (e.g. automation, innovation) and from policy (e.g., land-use regulation) shape economic outcomes. My contributions to these topics are primarily empirical in nature, applying existing methods and techniques to generate unique insights, which add to the relevant literature on these topics. The work utilize empirical settings and data sources principally from the U.S., U.K. and other developed-economy contexts, both for reasons of data quality/availability but also because the substantive processes that are under scrutiny here are better studied in advanced-economy settings. Although the work is applied in nature, the theoretical and analytical background motivating the analysis is intellectualized within classic economic geography and labour economic thought. I also engage with and rationalize my insights with related work from other disciplines in fields such as the Economics of Education, Housing Economics, and Macroeconomics.

Labor markets have been and continue to be profoundly influenced by technological change (Brynjolfsson and McAfee, 2014; Benanov, 2020). This is the case whether such mechanisms occur during the knowledge creation and experimentation process or their subsequent materialization into concrete automated processes. Furthermore, different groups of workers and those working in various industries may be differentially affected by the advent of such change and such outcomes are particularly shaped by and are manifested in urban environments. The first three papers of this thesis study this broad topic in depth though each paper deploys a unique lens to study such issues. The first paper principally seeks to examine local and urban-specific forces of technological change in understanding labor market dynamics across education groups. The second paper primarily exploits variations in robot use across industries to examine how automation shapes local labour market and wider economic performance at large and across different skill and sectoral groups. The third paper takes this issue further and adopts a non-spatial approach to understanding and explaining the labor market implications of sectoral spillovers stemming from automation. The fourth paper departs somewhat from the focus on labour markets and examines instead the impact of land-use regulations on local economic growth. The next section explains the focus and motivation of the four papers in more detail.

1.1 Chapters of the Thesis

In the first paper of the thesis, we attempt to explore the local determinants of the returns to college education with an aim to understand the local structural, economic and technological factors affecting relative wage differentials between college and non-college-educated workers in urban settings. In recent decades, workers across the education divide have been living through quite different urban experiences (Moretti, 2012). Those with and without college degrees have been sorting across cities with implications for the diverging fortunes of cities as well as for the fortunes of such workers. Educated workers have primarily been concentrating themselves in large, skilled, innovative cities leading to a divergence in outcomes including across earnings, house prices and wellbeing (Duranton and Monastiriotis, 2002; Moretti, 2012; Diamond, 2016). Studying the wage premiums to college education, we argue, can illuminate the determinants of urban within-locality inequality by skill groups (Glaeser et al., 2009) and better explain the main local causes of the diverging sorting patterns and urban experiences faced by workers across education groups. More importantly, it can inform us about how technological change (often perceived to be manifested in increased demand for skills) affects labour market outcomes across the urban metropolitan space. Our findings point to innovation, particularly increases in innovation intensity, as the leading culprit in driving a larger wage gap between workers of such groups. These processes are ever more magnified in cities with larger populations. In effect, this suggests a winner-takes-all dynamic: innovation activity create large wage premia to skilled workers in very large cities, which also experiences faster accumulation of knowledge through spillovers and higher productivity and wage growth.

The second and third chapters of the thesis relate to the labor market implications of automation technologies. In recent decades, the economy has seen a rise of many automated features and machines working themselves into the production process of goods and services across many domains. This has created unease among those currently in the workforce as many fear their jobs could one day be replaced by machines. If the automation capabilities of today perform tasks that is the same as those currently in the workforce, this can lead to a decline in labor demand as employers substitute workers with machines (Acemoglu and Restrepo, 2018). On the other hand, if such technologies perform new tasks that complement the existing task set of workers, this could result in positive productivity gains with little displacement potential (Ibid). We therefore empirically study automation developments, in particular, the advancements of a specific type of automation technology – industrial robots – exploiting two distinct angles and empirical approaches to examine the issue. Understanding how workers are affected by the advent of new automated technologies can help to illuminate the design of policies and institutions to aid their arrival or to mitigate their possible displacement effects.

For the first approach, we extend the local labor market framework previously used by scholars in the literature to the U.K., a developed economy with comparatively few robots in use though policymakers and stakeholders are keen to boost the automation capabilities of the country. We find little net effect in terms of wages and employment across labor markets though we document differential effects across sectors and occupations consistent with both productivity-enhancing features of automation as well as evidence of task displacement and reallocation. In the second approach, we apply input-output analysis to study the downstream labor market consequences from the advancements of automation technologies. The deployment of automation technologies in specific industries should lead to gains in industry productivity and this fact could also have downstream consequences as such productivity shocks spillover across sectors through industry linkages (Acemoglu et al., 2015; Autor and Salomons, 2018; Graetz and Michaels, 2018). Using a multi-country setting, we study such developments showing that the robotization of industries have positive implications for labor demand in downstream sectors. We show that such channels work through the price movements of the outputs (input) of supplier (customer) industries and document suggestive evidence that such gains to labor market outcomes are broadly shared across skill groups.

The final and last paper, which studies a distinct topic, concerns the implications of land-use regulation to local economic growth. While thematically different from the first three papers of this thesis, this topic is, nevertheless, an important area of concern for localities. Tight restrictions on land use limit the ease with which new housing developments can accommodate budding local demand; this, when accommodated by demand pressures, leads to high local house price responses, contributing to housing affordability problems across cities. Despite the potential to act as a binding influence on urban growth as a form of supply-side constraint restricting the efficient use of a critical input – land, land use regulation is actually positively correlated with high levels of economic activity as many of the most economically successful cities, observationally, are also the most restrictive ones (Gyourko et al., 2013; Hsieh and Moretti, 2019). This is despite the numerous past studies demonstrating land-use regulation's potential to dampen the construction and employment response to local demand (Mayer and Sommerville, 2000; Saks, 2008) as well as its damaging effects to the growth of certain sectors (Suzuki, 2013; Albouy and Elrich, 2018). Our findings yield no discernable impacts land use regulation, when viewed in relation to local demand, has on local growth outcomes at the economy-wide or at the industry level. A further exploration suggests that high land-use regulation combined with high demand pressures likely exert two countervailing forces to local economic outcomes with the sum of the two forces leading land-use regulation to have no net impacts to growth. High regulation paired with high demand reduces the employment and construction response from demand shocks, lowering growth than what it would be based on demand fundamentals alone. The same set of circumstances, however, also causes a disproportional house price response, which is then fed back into the real economy through consumption channels given the housing wealth gains and relaxed collateral constraints faced by local households (Mian et al., 2013; Mian and Sufi, 2014). An analysis of our specification absorbing local house price movements additionally affirms our hypothesis by teasing out these separate mechanisms.

1.2 Contributions and Afterthoughts

One of our main contributions to the wider topic on the labor market implications of technological change, particularly through the first chapter, is that we reinforce and complement the findings of past work on the local innovation-inequality link (Lee and Rodriguez-Pose, 2013) but produce findings specially pertaining to workers across the college/non-college education distribution. As the local returns to skill explain more than 50% of the variation in within-city inequalities (Glaeser et al., 2009), our findings additionally affirm the influence innovation (along with agglomeration forces) exert on widening local wage gaps. The knowledge creation process, generating relative winners and losers, induces wage outcome differentials that biases skilled workers. This can be because it is predominantly skill workers engaging in innovative activities and, to the extent that such activities have an economic payoff, this is reflected in their wages. The skill-biased nature of spillovers from innovative activity has also been documented through local employment channels, as increases in innovative, tech sector employment generate local wage spillovers that favor skilled workers working in local non-tradeable sectors (Kemeny and Osman, 2018). This additionally implies that it is also skilled workers with existing task content that are likely to be complements to those of innovative activity that are rewarded in the urban labor market. Our findings also relate to the wider literature on the spatial sorting patterns of college graduates (e.g. Abreu et al., 2015). Diamond (2016) argues that it is fundamentally local demand forces and the endogenous amenity responses that follow that have driven the urban sorting and welfare (wage + amenities) divergence by their college/non-college status. By studying the earnings premium for college education valued in the urban labor market and their local determinants, we have shown that local innovative activities taking place in large cities are, in part, driving this demand and reinforcing such patterns of sorting and migration. These findings suggest scope for government policy to counteract the path-dependent nature of innovation clusters being locked up in large cities by rerouting public investments towards smaller, educated hubs ripe for development and spread out the economic opportunity along the lines Gruber and Johnson (2019) have proposed.

The second main takeaway from our analysis of technological change in terms of automation technologies as expressed in Chapters 2 and 3 are that automation actually produces more nuanced outcomes to labor markets than the existing prevailing evidence would suggest (e.g. Acemoglu and Restrepo, 2020) and our analysis of particular channels and contexts actually point to broadly positive effects to labor demand through direct and indirect productivity mechanisms. Our results in Chapter 2 point to positive influences on manufacturing employment from robotics automation directly in the U.K. as manifested in local labor markets consistent with strong productivity influences at low rates of automation (Cali and Presidente, 2022). In Chapter 3, we uncover an underexplored channel in which the deployment of industrial robots can in fact additionally lead to higher labor demand in downstream sectors as the productivity benefits of automation technologies are felt across sectors. In addition, our analysis is also consistent with the framework established by Autor and Salomons (2018), which emphasize the labor market reallocation dynamics as workers gradually transition away from sectors most exposed to automation to those that are less effected by such technological shocks. Our differential results for routine and non-routine groups of workers support this notion and such dynamics are also additionally affirmed by the results found in Germany for industrial robot adoption specifically (Dauth et al., 2021). Our findings on this strand of work demonstrate that automation technologies' implications to labor markets, particularly in the form of industrial robots, are more positive than expected as 1) they can in fact be beneficial for workers through productivity channels and 2) displacement effects can be smoothed out through normal labor market transition and reallocation mechanisms.

Finally, the main implication from the last chapter of this entire thesis is that local economic growth is ultimately driven by demand forces and has little to do with supply-side constraints such as land-use restrictiveness. However, our results, nevertheless, illustrate that land-use regulation can alter the composition of growth as it could determine whether demand shocks are manifested in growth through higher eventual employment and construction (low regulation) or whether such shocks translate to higher consumption levels from existing residents (high regulation). More work may be needed to test these mechanisms at work in practice.

The approaches used in this research have scope to be further utilized to analyze other specific forms of technological change as well as in other economic contexts. For instance, the local labor market approach we adopted in Chapter 2 has been used to explore the labor market impacts of Artificial Intelligence – another distinct form of technological change (Acemoglu et al., 2022) and others have continued to extend and apply the local labor market approach to additional countries in the analysis of industrial robots such as Japan and Indonesia (e.g. Adachi et al., 2020; Calì and Presidente, 2022). As for the input-output framework, more can be done to assess the spillovers associated with technological shocks using this approach. In addition, there is also further scope to incorporate a geographical element in assessing such spillovers by zooming in on the spatial manifestation of industry linkages inferred through local industry composition as with Acemoglu et al. (2015). Lastly, I really hope this thesis can be useful for those that find these topics interesting. Enjoy and happy reading!

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Chapter 2: Local Innovation and the College Wage Premium: Evidence from the USA

2.0 Abstract

Cities and regions display sizeable and systemic differences in the returns to schooling, contrary to the predictions of spatial equilibrium. This study explores the role of innovation and other local features in explaining the returns to attending university across U.S. metropolitan areas. Using a two-step approach that controls for worker and firm sorting across occupations and cities respectively and complementing the analysis with an instrumental variable approach, the large gap in college – non-college pay appears to be largely driven by differences in the intensity of innovation activity locally. These patterns also appear to be magnified in larger cities consistent with the role of agglomeration in facilitating knowledge spillovers. Our results underscore a need for innovation policies to consider their local distributional consequences, particularly across the education divide, and highlight the rationale for a geographically more equitable dispersion of research and innovation funding.

2.1 Introduction

Spatial equilibrium theory predicts the equalization of real wages across locations as differences in local wages that arise would be mediated through migration (Roback, 1982). Similar arguments can be made for the returns to schooling as economists often assume that such returns are invariant across locations (Black et al., 2009). Despite such predictions, the gaps in the wage returns to education across cities are often sizeable. Cities today differ along various economic dimensions including size and skill composition, which should lead to differences in the value of education in the local labor market. Motivated by these observations, this study seeks to understand the spatial determinants of the wage premium for college education across cities in the United States.

Understanding the college wage premium and its variation across geographies is important for several reasons. Examining the determinants of the local returns to education can provide further insights on the within-city differences in wages across the skill divide and on the distributional impacts of local public policies. As Glaeser et al. (2009) documents that variations in the returns to skill explain over 50% of within-city inequality[1], the analysis of the determinants of the localized returns to college has the potential to illuminate the sources of the leading drivers of local inequality inside cities, particularly among skill groups. Second, college graduates have an incentive to sort to locations to maximize their real earnings but also to locations where the expected returns to their education is highest. Hence, understanding sources of high returns in cities could provide important clues as to the sorting patterns of college graduates and the eventual spatial distribution of skill across the country.

Despite the salience of these issues, especially at a time of significant political and socio-cultural polarization across regions (Rodriguez-Pose, 2018), there is surprisingly little research seeking to explain the observed variation in the returns to college education across space. Past research has demonstrated the importance of amenities in explaining local wage returns to education (Adamson et al., 2004; Black et al., 2009). In this paper, we provide a more comprehensive analysis of the role of city-level characteristics on the wage returns to college education and deviate from past studies by focusing on the role of innovation and agglomeration in conjunction with other local characteristics. Using micro-data from the American Community Survey (ACS), we estimate city/year-specific returns to college for 265 U.S. metropolitan areas (MSAs) over the period 2005-2015 and examine their locational drivers. Our study improves on the scant past research in a number of ways. First, by utilizing yearly panel data that covers most metropolitan areas in the U.S., unlike past studies, thus giving more variation and allowing us to control for unobserved city-characteristics and national influences. Second, methodologically, by deploying a two-stage approach which allows us to examine in more detail not only the direct effects of various characteristics but also their combined impact (interaction effects) – and to treat more directly issues concerning endogeneity as is explained later.

Our results show that innovation raises the college wage premium at the local level as a 10% increase in patenting intensity raises the returns to college education by up to 0.6 percentage points. We also explore heterogeneities in the returns to education finding that larger cities magnify the impacts of innovation on the wage returns to college consistent with existing evidence on the knowledge diffusion and spillover mechanism of agglomeration. Ultimately, our findings imply that innovation, by raising the wage premiums to education, could be the leading culprit in driving

[1] Glaeser et al. (2009) shows that there is a 73% correlation between the estimated returns to college and the local Gini coefficient across U.S. metropolitan areas.

a wage gap across the college-educated divide reinforcing within-city inequalities across skill groups. This suggest that public policies meant to enhance local innovative capacity or attract innovative companies, while benefiting local economies, could have distributional consequences creating more economic distance between the skilled and unskilled. Hence our findings imply that the design of spatially targeted innovation-promotion policies should also consider their distributional consequences. The fact that innovation and urban scale work jointly to create persistently higher wage premiums in cities is suggestive that large, innovative cities generate equilibrium wage outcomes that serve as magnets for college graduates, with long run implications on their sorting patterns. A continued concentration of innovation in dense cities, economically favoring those with skills, may further contribute to the observed economic and wellbeing gaps between college and non-college workers (Moretti, 2012; Diamond, 2016) and the economic and social polarization across cities and regions (Rodriguez-Pose, 2018). Despite the potential efficiency gains driven by the spatial concentration of innovative tasks (Moretti, 2021), Counteracting such consequences may necessitate policy interventions that incentivize the diffusion of innovation across space. This may include policy efforts aimed at reinvigorating innovation in America’s smaller but promising cities outside of the biggest metropolises (Gruber and Johnson, 2019).

Our findings complement previous work in explaining wage disparities across locations (Duranton and Monastiriotis, 2002; Combes et al., 2008; De la Roca and Puga, 2017). Our study is also related to the literature on the effects of education on earnings (Card, 1999), on wage polarization across the skill distribution (Katz and Autor, 1999; Goldin and Katz, 2007), on national trends in the returns to skill (Beaudry et al., 2016) and on the distributional effects of local innovation (Lee, 2011; Lee and Rodriguez-Pose, 2013). The next section reviews the brief literature on schooling returns across locations and discusses how local features influence region-specific college wage premiums. Section 2.3 introduces the data and methodology of the paper and Section 2.4 presents and discusses the results. Finally, Section 2.5 concludes.

2.2 Literature and Discussion

2.2.1 Literature

The returns to education is understood to be the increase in wage earnings from possessing additional years (or degrees) of education and is typically estimated with a Mincer-type earnings regression.[2] Hanushek (1973) is among the first to consider the role of regions in determining local schooling returns finding that such differences are mostly attributable to regional economic structures that lead to differences in the demand for skilled labor. Beeson (1991) provides among the first metropolitan-specific estimates of the returns to additional years of schooling in 46 cities in 1980. Estimates range from 1% to 5% and their variation, according to Beeson (1991), is primarily explained by amenity differences. Adamson et al. (2004) finds that the largest U.S. cities actually exhibit a smaller wage gap across education groups as they contain a richer set of amenities. Perhaps most closely related to our work, Black et al. (2009) estimates metropolitan-specific returns to college in the U.S. between 1980 and 2000. Their estimates of the wage premium range between 40% to 60% for selected cities. The most surprising result, perhaps, is that the highest-wage cities tend to have the lowest returns to education. This, according to Black et al. (2009), can be reconciled by the amenity-rich nature of low-returns cities. Glaeser et al. (2009) examines the determinants of inequality within cities and finds that differential returns to college education can explain much of the differences in within-city wage inequality. Moretti (2013) finds a positive connection between the share of local college-educated workers and the college wage premium, arguing that differences in the returns to college are predominantly a demand-driven phenomenon. Past research, indeed, has demonstrated that there exists substantial heterogeneity in the education wage premium across cities and many local characteristics, particularly amenities, can in fact influence local education returns. The next section reviews the role of innovation, population and other local characteristics that could influence education returns.

2.2.2 Local Features and Returns to Education

Research on the link between innovation and wages across the skills distribution has predominately centered around Skilled-Biased Technological Change (SBTC), where technological change in recent decades have complemented workers at the high end of the skills distribution while serving as substitutes to the work of middle-skill groups (Acemoglu, 1998; Autor et al., 1998; Berman et al., 1998). Innovative activity produces gains that are likely to accrue to individuals with complementary skills that have the capacity to utilize the knowledge spillovers associated with proximity (Lee and Rodriguez-Pose, 2013). These dynamics should play out most

[2] See Heckman et al. (2006) for a review.

prominently in cities, where dense urban local markets facilitate the learning mechanism and the faster accumulation of knowledge across firms and workers (Jaffe et al., 1993; Duranton and Puga, 2004). Workers in cities are shown to be exposed to more knowledge spillovers compared to their rural counterparts (Glaeser and Mare, 2001) and they also acquire more economically valuable skills the more time they spend in larger cities (De la Roca and Puga, 2017). Innovative firms also want to collocate in cities, especially skilled cities, to aid the innovation process, as workers can convey complex tacit knowledge with each other to facilitate the development of new products and processes (Storper and Venables, 2004). Hence it may be no coincidence that the vast majority of innovation and technology employment is geographically concentrated in just a handful of cities (Moretti, 2004b; Moretti, 2012; Carlino and Kerr, 2015). Skilled workers also enjoy an earnings premium by residing in tech-driven metropolitan economies (Echeverri-Carroll and Ayala, 2009). Innovative activity in cities, which involves the creation of new knowledge, should disproportionately benefit college-educated workers, who are more likely to be involved in its production and gain from it. This means that innovative activity in a city should raise the returns to higher education not only through a demand channel (raising the relative demand for skills) but also over and beyond that – e.g., by creating rents that can then be shared with those skilled workers involved in the creation of new knowledge (rent-sharing) or by forcing firms to offer higher premia under a signaling or efficiency wages rationale (raising skilled workers' effort to innovation). Given these discussion, we hypothesize that innovation has an influential role in raising the returns to college.

Another local influence that could raise the wage returns to skill is the role of urban scale through agglomeration economies. Workers in larger cities earn more as they facilitate the positive productivity effects of proximity through matching, sharing and learning mechanisms (Duranton and Puga, 2004). A doubling of city size, for instance, should raise productivity and wages by up to 3 to 6% (Combes et al., 2008; Combes and Gobillon, 2015). Urban scale would be positively related to education returns if agglomeration is skill-biased and numerous studies have indeed affirmed this notion. Rosenthal and Strange (2008) find that the observed wage advantages associated with city size are magnified by more than 20% for skilled workers. Glaeser and Resseger (2010) show that the wage advantages to city size vary positively by the share of educated residents. Groot and De Groot (2014) find that the estimated agglomeration elasticities with respect to wages vary by at least 7 percentage points from the most to least educated workers. These findings highlight the possible associations between city size and local education returns. Furthermore, educated workers benefit more from agglomeration, in part, through a faster accumulation of knowledge and information spillovers relevant for production processes in cities (Lee and Rodriguez, 2013; Groot and De Groot, 2014). This is suggestive of potential synergies between innovation and agglomeration economies in determining the local returns to education.

Additionally, there are other local features that could influence the wage returns to education and skill and we briefly review them to justify their eventual inclusion in our specification. One such local characteristic is the desirability of locations or local amenities, which can determine local wage differentials as workers substitute high nominal wages for desirable amenities across locations (Roback, 1982). Roback (1988) and Black et al. (2009) show that local amenities can also explain education returns if workers have differential tastes for amenities. Skilled workers may place a greater value on amenities, leading amenities to be associated with lower returns as skilled workers forgo a higher portion of wages to reside in amenity-rich places (Gagliardi and Schlüter, 2015). This hypothesis has been supported by Diamond (2016), who finds U.S. college-educated workers to be more sensitive to local amenity differences, and Gagliardi and Schlüter (2015), that find skilled British workers value local amenities higher. Studies examining the link between local amenities and education returns directly also arrive at similar conclusions (Beeson, 1991; Adamson et al, 2004; Black et al., 2009). As local amenities can comprise of various features including physical attributes i.e. topography and weather along with non-physical attributes i.e. crime rates, schooling quality, and consumption characteristics (Glaeser et al., 2001; Albouy, 2008), we follow Black et al. (2009) and approximate the general value of local amenities with house prices.

Another feature that could determine local education returns is the quantity of the educated workforce itself. The local share of the college workforce could influence the returns to education through a classic supply effect. Conventional quantity-price relationships suggest that when the quantity of college graduates increase, its relative price – and thus the education wage premium – should decrease (Katz and Autor, 1999). Local college share could also determine education returns through spillover mechanisms as concentrations of human capital generate positive economic externalities locally (Lucas, 1988; Rauch, 1993; Monastiriotis, 2002; Moretti, 2004b). Increases in the local share of educated workers raise the wages of all workers within cities, regardless of their skill level, and boost local output (Rauch, 1993, Moretti, 2004c). Spillover effects could lead to greater returns if the positive spillover forces are skilled-biased (Moretti, 2004a). In addition, high local shares of college workers and the presence of high returns could also be reflective of localized labor demand (Moretti, 2013; Diamond, 2016). Given these discussions, we incorporate local amenities, college share, and local demand, measured through local wages and unemployment, in our specification along with our main outcomes of interest.

2.3 Data and Methodology

2.3.1 Data

The main data source in this paper comes from the American Community Survey (ACS), between the years 2005 to 2015 (Ruggles et al., 2019). The ACS is an ongoing survey conducted by the U.S. Census Bureau to collect detailed demographic, social and economic information of individuals and households. [3] As the ACS is meant to replace the long form version of the Census, the survey provides the same information as those found in past Censuses including information on income, education, age, gender and other labor market characteristics as well as their geographic information such as counties and states of residence. We group our data at the metropolitan level, following Metropolitan Statistical Area (MSA) definitions. MSAs are a compilation of U.S. counties usually centered on a major city with high degrees of economic and social integration across adjacent communities (OMB, 2010). They are drawn to reflect economic boundaries as the vast majority of households both live and work in the MSA. We recover data on 265 MSAs throughout the 11 years of our sample. We restrict our sample to workers between the ages of 25 and 54 earning positive income to avoid capturing wage effects from those enrolled in education and nearing retirement. As our study analyses the returns to college; those with education levels below that of a high school degree and above a bachelor's degree are excluded. The median number of individuals in each MSA-year pair is around 1,000 with the lowest having approximately 200 individuals. MSA characteristics, including college share, earnings, and unemployment among others, are computed by aggregating individual responses for each MSA-year using individual and household sample weights.

[3] This is done by surveying 1% of U.S. households every year or approximately 3.5 million households. Household and person weights are provided by the ACS via the IPUMS portal to reflect the likelihood of being sampled.

2.3.2 Methodology

We utilize a two-step approach in our analysis. This two-stage approach has its roots in past research estimating the external returns to education at the region (industry) level by estimating a wage regression in the first stage with region (industry) fixed effects and explaining their variation in the second stage (Winter–Ebmer, 1994; Sakellariou, 2001; Monastiriotis, 2002; Sakellariou and Mayasami, 2004). In this literature, as the private returns to education at the worker level are absorbed by the education coefficient in the first stage, the average effects of education on region (industry) fixed effects in the 2nd stage could be interpreted as the external effects associated with education.

In our study, we deploy the same approach on the estimated college education wage premium directly. The first step involves a variant of the mincer earnings regression at the worker level estimated for each MSA-year. We derive two main specifications from the first stage with a Simple mincer and an Extended version, which includes additional controls including occupation and industry effects at the individual level. This distinction has the added advantage of accounting for occupation and industry sorting that explains wage differentials across education groups. Controlling in this way for confounding factors affecting the college premium at the individual level, we subsequently deploy our estimates of the college premium at each year-MSA cell in a 2nd stage and regress them against a range of city-level characteristics. Our 2nd-stage model includes year and MSA fixed effects, to account for unobservable nation-wide temporal influences and for time-invariant city-specific characteristics. Our 2nd-stage models include additional controls for local industry and occupational shares, to account for variations in the extent of geographic clustering of specific industries and occupations that could influence local returns. Given our interest in a range of variables with innovation as the focal feature, the two-stage approach allows us more flexibility in our estimations (including the use of instrumental variables that controls for endogeneity) compared to the alternative of a single-stage approach whereby the area-level characteristics would be interacted in the individual-level regressions (first stage) with the education dummy (as in Adamson et al., (2004)). It should be noted that our two-stage approach does not directly address the issue of endogeneity with regard to education (ability selection into education), which concerns much of the literature on estimating the causal wage impact of education (e.g. Card, 1999; Heckman et al., 2018). To the extent that this bias is time-invariant within cities (and/or space-invariant over time), this would not present a problem in our analysis, as it should leave our second-stage estimates unbiased.

2.3.3 Model

Our first-stage regression takes the following form shown in Equation 1:

$$\text{Ln}(Hourly\ Wage)_i = \beta_1 College_i + \beta_2\, S_i + \beta_3\, E_i + \varepsilon_i \qquad [1]$$

where the natural log of computed hourly wages for all worker 'i' is regressed on a set of individual characteristics.[4] The variable of interest 'College' denotes a dummy variable taking the value of 1 if the individual has a college degree (and zero otherwise).[5] 'S' denotes a vector of variables including age, age-squared and gender, which represents the variables covered by the Simple Mincer specification.[6] 'E' is a vector of variables representing the Extended version of the Mincer specification, which additionally controls for occupation, industry, marital status, and race.[7] 'ε' denotes other unobserved worker-level characteristics in the wage regression. We estimate Equation 1 at the individual level separately for each MSA-year cell. The estimated coefficients 'β_1' is then extracted and becomes the dependent variable in the 2nd stage as shown in Equation 2:

$$\widehat{\beta_1}_{mt} = Inn_{mt} + Pop_{mt} + HP_{mt} + Edu_{mt} + D_{mt} + OI_{mt} + \gamma_m + \delta_t + \varepsilon_{mt} \qquad [2]$$

where '$\hat{\beta}_1$', extracted from the first stage, represents the percent increase in wages from holding a college degree in metropolitan area 'm' year 't' and is regressed on a set of city-level characteristics. 'Inn' represents levels of innovation intensity, captured by the log number of population-adjusted utility patents issued.[8] 'Pop' denotes city population while 'Edu' captures the share of the

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[4] Nominal wage is used here as the regression is computed by each MSA-year cell.
[5] Those with four or more years of undergraduate education are assumed to hold a college degree.
[6] Our analysis includes both male and female workers, groups that may exhibit differential labor market outcomes. As our primary outcome of interest is differences across cities in returns, labor market differentials across gender divides would unlikely affect our results.
[7] While our specification do not control for differences in the type and quality of 4-year college degrees, our Extended specification, taking into occupation and industry effects, should appropriately capture such differences to the extent they reflect the sorting of individuals into various sectors and jobs.
[8] A limitation of using patenting activity to approximate the level of innovative activity in a city is that it may exclude innovation in certain service sectors that rely primarily on trademarks or copyrights to secure intellectual property rights.

population over the age of 25 with a college degree. 'HP' denotes local house prices, which is meant to reflect local amenity values. 'D' is a vector capturing local demand pressures including the local log real weekly wage (in 2015 Dollars) and the unemployment rate.[9] 'OI' refers to the vector of industry and occupation employment shares using ACS industry and occupation codes. As noted already, industry and occupation shares are included to mitigate the effects of the geographical sorting and clustering of certain industries and occupations. Metropolitan area 'γ_m' and year 'δ_t' fixed effects are additionally deployed to absorb time-invariant and year-specific features in the specification respectively. Finally, 'ε_{mt}' represents the error term in the regression. The specification is also weighted by the inverse of the standard errors of the college returns coefficient '$\hat{\beta}_{1_{mt}}$' from the 1st stage regression and the standard errors for the 2nd stage analysis are clustered at the metropolitan area level.

2.4 Empirical Results

2.4.1 The College Premium Across Metropolitan Areas

Our first-stage specification consist of 2,795 regressions at the MSA-year level (265 MSAs across 11 years)[10] recovering the same number of education-wage coefficients. In Table 2.1, we present these results in summary form, giving the min, max, mean and standard deviation values of our estimates and our explanatory variables of interest across the distribution of MSAs for all years. Rows 1 and 2 show the estimated college returns for the Simple and Extended Mincer specification respectively. The unweighted average college returns across cities from 2005 to 2015 for the Simple Mincer, with age, age squared and gender as controls, stands at 38.5%[11] while the estimated gains to college derived from the Extended Mincer, additionally controlling for marital status, race, industry, and occupation, stand at 25.3%. The decline of average returns by more than 30% when utilizing the Extended Mincer suggest strong compositional features in the returns to college i.e. that the raw returns to college is determined, in a large part, by occupation and industry-specific influences. The comparison across the estimates in the 1st stage do suggest that the Simple

[9] Unlike Moretti (2013), these measures capture general local demand pressures and do not capture skill-specific demand pressures.
[10] This is an unbalanced panel as not all MSAs are available every year.
[11] Our college return estimates using the Simple Mincer specification is largely in line with those found in past direct estimates of the college wage premium across cities (Black et al., 2009; Glaeser et al., 2009) with observed systemic differences in the wage returns to college going back to at least 1980.

Mincer estimate of the returns to college, as we've hypothesized previously, capture, in part, sorting effects across occupations and industries along education divides. Such differences further motivate our approach to net out such factors in our analysis with the use of the Extended Mincer. To further probe the distributional discrepancies between the Simple and the Extended specification, Figures 2.1 and 2.2 plot the frequency distribution of the estimated returns of both specifications in 2005 and 2015. The returns to college education are in fact *not* equalized across locations as the returns for both estimates actually display a wide variability across cities following a normal distribution and such patterns have persisted throughout the study period. Note that the distribution of returns follows nearly the same pattern between the Simple and the Extended Mincer estimates, albeit converging around a different mean. This is confirmed by the nearly identical observed standard deviation between the two estimates in Table 2.1. The fact that such variability of returns across cities remains even after deploying such an extensive specification in the 1st stage with the Extended Mincer is evidence that local factors do indeed play an influential role in determining the returns to college locally and provide further motivation for our analysis.

Table 2.2 present the top 20 highest ranked cities by their levels of estimated returns *and* by compositional features such as population and wages in 2005. From this table, it is telling that cities with the highest observed rates of returns to education are almost never those with large populations or with high average wages. None of the top 20 cities in terms of estimated returns for the Extended Mincer are represented in high-wage or large-population cities. By contrast, 7 of the largest U.S. cities are also present in the top 20 cities in terms of earnings including many well-known, emblematic examples such as New York, Chicago, San Francisco, among others. The tight urban scale-wage association is consistent with strong urban agglomeration forces though this does not necessarily translate to an additional added association with high returns to college education. Despite earlier discussions of a potential link between urban scale and college returns, expected returns to college at the top of the returns distribution is not conventionally related in rank terms to cities with high incomes or large populations.

How do the local returns to college correlate observationally with the characteristics of cities? Figures 2.3 through 2.6 plot the linear relationship between the Simple and Extended college returns estimates with the various local characteristics of interest for the years 2005 and 2015. For the year 2005, the correlational relationships between the Simple (Figure 2.3 and Extended (Figure 2.4) specification is not very different from each other. College share and house prices, reflecting amenity differences, are mildly associated with declines to returns for both specifications while population is weakly associated with higher returns consistent with earlier discussions. Patent intensity (capturing innovation), meanwhile, relates negatively with returns contrary to our earlier hypothesis. However, by 2015, many of these correlational relationships have reversed course for the Simple Mincer (Figure 2.5) as the estimated returns are uniformly positively associated with all local characteristics of interest. This is in contrast to the Extended Mincer estimates (Figure 2.6), whose correlational relationships with local characteristics have not deviated much between the two years and display much weaker associations to every local characteristic than compared to the Simple Mincer in 2015.

The strong associations with local characteristics found for the Simple Mincer paired with the much more muted correlational findings for the Extended Mincer suggest that much of the naïve associations between college returns in the Simple Mincer estimate and various city-level characteristics reflect industry and occupation effects to individual wage outcomes. Furthermore, the high volatility of correlational findings for the Simple Mincer across years is suggestive of the specification capturing highly cyclical components of education returns possibly relating to demand along with sectoral trends. Purged of industry and occupation effects, the Extended Mincer, we argue, allows us to recover a more accurate *and* stable estimate of the true returns to college and this will be the main 1st stage estimates of the college wage premium used in the empirical analysis. Moving beyond these observational associations, in the next section we examine these relationships in conjunction through our econometric investigation.

2.4.2 Econometric Results

Our econometric analysis makes the estimated year/MSA-specific college returns a function of a series of city-level characteristics. We model these sequentially, as depicted in Table 2.3, where the outcome of interest across all specifications is the Extended Mincer with individual controls on age, age-squared, gender, occupation, industry, marital status, and race in the 1st stage. Column 1 in Table 2.3 shows the OLS estimates of the 2nd stage analysis where the regressors are our main explanatory local outcomes of interest e.g. innovation intensity and population. The results are particularly informative. As we see in Column 1, innovation intensity plays a key role in raising education returns while urban scale (e.g. population[12]) do not play a role in explaining the distribution of estimated returns to college. The finding that city-size is not associated with higher returns is somewhat surprising, given the earlier discussions on the skill-bias nature of agglomeration (Rosenthal and Strange, 2008; Glaeser and Ressenger, 2010) and the extensive literature on city-size and urban wages (Melo et al., 2009). It appears that although larger urban areas have higher wages, they do not have more dispersed wage distributions (along the college – non-college dimension). In Column 2, we further incorporate additional local features in the specification as discussed earlier including amenities, college share and local demand pressures. We find here that local amenities are found to be negatively associated with the college premium, which is consistent with past studies and the interpretation that skilled workers substitute higher returns (relative wages) for better amenities (Black et al., 2009). In Column 3, we further introduce local occupational and industry shares as controls. In this specification, amenities no longer meaningfully explain differences in the college wage premium. Meanwhile, local innovation intensity is meaningfully and persistently associated with higher returns to college education across all three specifications. In our preferred specification (e.g. Column 3), a 10% increase in innovation intensity is associated with a 0.6 percentage point increase in college returns. These results are also consistent with those found for the specification where college returns is estimated with the Simple Mincer in the 1st stage, which we report in Table A-1[13] of Appendix A-1. This is an important finding. Given that our regressions control for factors such as labor demand (local unemployment and wages) and the skill (share of college graduates) and sectoral-occupational composition of the workforce, we are tempted to conclude that innovation does not only raise the relative wages of college graduates through a demand channel (raising labor demand for skilled workers) but also through a rent-sharing channel (innovation raising the rents to be shared with those – the skilled – working in innovative segments of the local economy). It follows that innovation activities within cities can have important distributional consequences over and above ones that operate through shifts in the relative demand for labor.

Given the potential significance of such a conclusion, we extend our analysis to examine further the robustness of our findings concerning the impact of innovation on the college premium. Our main consideration has to do with the potential endogeneity of innovation to the college

[12] Given our controls for MSA fixed effects, This actually captures population density (as MSA area is fixed over time).
[13] Table A-1 replicates Table 4 but instead assesses the College Returns estimated with the Simple Mincer.

premium. Local innovation is, of course, not random across cities and is jointly determined by local firms and the local workforce engaging in innovative activities. As such, local innovation could be associated with unobserved characteristics in the composition of the local workforce that could bias the relationship between innovation and the college wage premium. For instance, changes in local innovation could lead to differential sorting patterns of college graduates based on unobservable features across cities, which influences its relationship with the returns to college education locally.[14] To deal with possible endogeneity issues between local innovation and the college wage premium, we implement an instrumental variable approach, instrumenting for local levels of patenting using predicted levels of patenting from a Bartik-style shift-share instrument, based on a detailed breakdown of patenting by patent class in each metropolitan area inspired by Hornbeck and Moretti (2022). Our approach relies on the set up shown in Equation 3.

$$\widehat{Patent}_{mt}^{IV} = \sum_k Patent_{kmt_0} * \frac{Patent_{Nkt}}{Patent_{Nkt_b}} \qquad [3]$$

We predict the number of patents in each metropolitan area ‘m’ at time ‘t’ by taking the number of patents in patent class ‘k’ in metropolitan area ‘m’ at the base year ‘t_b’[15] and multiplying this by the national-level growth rate[16] of patent class ‘k’ between time ‘t’ and the base year ‘t_b’. The local innovation IV ‘$\widehat{Patent}_{mt}^{IV}$’ is then population adjusted and logged transformed. This instrument introduces variation that is relevant and plausibly exogenous by interacting the past stock of patent levels with national-level growth rates of each patent class unrelated to local conditions. Our IV estimates are reported in Column 4 of Table 2.3. The results from this exercise largely remain consistent with the OLS estimates previously reported in Column 3. Only innovation intensity exerts an influential effect on the returns to education across cities while no other local characteristic is meaningfully associated with college wage returns. The consistency, in terms of statistical significance, direction and magnitude, of the coefficients between the OLS and IV estimates demonstrates that the estimated effects of innovation on local college returns yield a plausibly causal interpretation.

[14] The presence of local innovation could for instance encourage the in-migration of college graduates, who are unusually sensitive to or compatible with the innovative activities of specific cities. This could downwardly bias the true effects of local innovation on the wage gaps between the skilled and non-skilled.
[15] Base year is the year 2000.
[16] National-level patenting of patent class ‘k’ is inferred by summing all the patents in patent class ‘k’ in all metropolitan areas ‘m’. By default, we ignore patenting in rural areas for the construction of our national-level patenting outcomes.

As a last extension to our analysis, we want to explore further the role of innovation in influencing the returns to college across cities. As indicated from our earlier results, an interesting – if quite puzzling – result from our analysis is that city size is not statistically associated with higher (or lower) college premia. However given our discussions earlier, there may be possible synergies between the two local forces where both work to jointly influence local education returns. City size may not influence returns in its own but rather serves as a conduit in strengthening the innovation-wage premium link given the key role knowledge and information spillovers play in agglomeration processes. In addition, it is also empirically shown that innovation activity has higher intensity in larger cities and that it is highly agglomerated spatially (Audretsch and Feldman, 2004; Carlino and Kerr, 2015). Given these considerations, we hypothesize that the relative wage gains of educated workers from local innovation could be higher in larger cities.

In this last piece of analysis, we examine whether the measured effects of innovation on the college premium varies by city size. In Columns 5 and 6 of Table 2.3, we hence extend our estimating model adding an interaction term between the two variables in both our OLS and IV specifications respectively.[17] Our results indicate a statistically meaningful and strong association between the interaction of innovation intensity (patents) with city size (population) and the size of the college premium – with the effect of innovation being sizably amplified in larger cities. Specifically, on the basis of the results presented in Columns 5 and 6 of Table 2.3, moving from the 25th percentile to the 75th percentile of the city size distribution magnifies the effects of innovation on returns by at least 0.55 percentage points from a 10% increase in innovation. To show the relative magnitude of this result, in Figures 2.7 and 2.8 we present a graphical depiction of the heterogeneous effect of innovation on college returns at various city sizes, based on the estimated marginal effect of innovation from the specification which includes the interaction term.[18] The result is very telling. While innovation has a statistically positive effect on the college premium *on average* (as shown in Columns 2-4 of Table 2.3), the effect is only significant (and grows larger) for large cities. In Figures 2.7 and 2.8, the marginal effect only starts to become statistically significant for cities with populations above the 75th percentile of the city size distribution.[19] It follows that the positive influence of innovation on college returns is almost exclusively driven by the largest cities.

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[17] Values of all variables are demeaned.

[18] Note that, as the values are demeaned, a city with a population value of 0 refers to the mean-size city.

[19] This threshold in which this corresponds to in the specification is a demeaned log population of 0.5

This puts into a completely different perspective our earlier findings. Whereas innovation is an important driver for intra-city wage inequalities along the college – non-college dimension, this only materializes in the largest of cities, where – unsurprisingly – most innovation activity is concentrated. In essence, this represents a threshold type effect, whereby the impact that innovation may have on the college premium is only activated in cities that have reached a sufficiently large scale. As Moretti (2021) has shown that the gains to innovation are greater in larger cities, we interpret this finding as offering further support to our earlier conclusion that the estimated link between innovation activity and the college premium reflects predominantly a potential rent-sharing mechanism.

2.5 Discussion

Our findings, showing that local innovation intensity to be driving a wage gap between skill groups, are related to a broader literature on the impacts of local innovation on local inequality (Lee, 2011; Lee and Rodriguez-Pose, 2013) as they are largely complementary to those found by Lee (2011) and Lee and Rodriguez-Pose (2013) that found increases in wage inequality arising from local innovation. Exploring specifically the wage gap effects from local factors across college educated and non-educated groups, our analysis additionally affirms the notion that the wage gains to local innovation disproportionally flow to college-educated workers and that local innovation acts as a driving force in reinforcing local wage inequality across the skill distribution.[20] Hence, our findings on innovation and local college returns serve as a cautionary note for policy makers wishing to enact innovation-promoting policies or attract workers and firms engaging in innovative activities. While a successful policy effort to boost local innovative capacity could bring about gains in local economic outcomes in terms of productivity and employment, the skilled-bias nature of innovation to relative wage differentials locally creates further economic distance between the skilled and unskilled. As the local gains from innovation are highly uneven, the design of innovation-promoting policies may warrant additional remedial levers to minimize its distributional consequences locally. This may include partnerships between local governments and innovative firms to establish opportunities for local residents to upgrade their skills in such a

[20] There is evidence that local innovative activity may still benefit low-skilled workers through increases in employment through a multiplier effect (e.g. Moretti, 2010; Lee and Clarke, 2019).

manner that would be complementary to the existing set of local innovative tasks or to allow them to participate in the innovation process directly.

Our findings also have implications for policies across cities and regions. Innovation's role in generating high local education wage returns further incentivizes the continued agglomeration of skill in large, innovative cities. Given the spatial concentration of innovation and the diffusion of knowledge spillovers, which are primarily local in nature (Jaffe et al., 1993), the local wage benefits of innovation to skill and its amplification in large cities serve to lock-in the benefits of innovation in selected cities, with consequences for inter-regional economic differentials. Such forces may be further exacerbated by the potential migration and sorting patterns of college-educated workers in the wake of innovation-inducing high local returns. The resulting spatial equilibrium implies further gaps between a handful of large, skilled and tech-oriented economies and the rest of the country consistent with the Great Divergence phenomenon in the U.S. documented by Moretti (2012) where American cities and regions are precisely polarizing based on skill and innovation differences. These patterns also carry significant socio-cultural and political consequences (Rodriguez-Pose, 2018) and may warrant corrective policy actions. Given the productivity and efficiency gains from the concentration of research and innovative activities (Moretti, 2021; Gruber et al., 2022), the appropriate action in light of these findings is not to actively reduce the innovation intensity in existing agglomeration clusters but rather to reorient public investments that would expand the innovative capacity in other smaller but promising cities across America (Gruber and Johnson, 2019). Gruber and Johnson (2019) have called for up to 200 Billion dollars in public R&D funding distributed towards educated, low-cost cities outside of coastal tech-driven economies with high growth potential. Policy efforts along these lines could be a good first step to redress the potential spatial imbalances brought upon by the wage dispersion effects of local innovation.

2.6 Conclusion

Despite the predictions of spatial equilibrium, there persist large differences between the returns to schooling across cities. Our paper provides among the first studies to estimate the returns to college for the vast majority of U.S. urban areas and explain their variation across an array of city-specific dimensions, with a focus on innovation as a driving force. Contrary to past findings that have shown amenities as the leading driver of return differentials across space, we instead find that only innovation intensity has an influential role in raising the local returns to college. Local innovation has a uniformly positive role in raising the returns to education and the effects of innovation on returns also increase by city size.

By raising the returns to education in certain geographies, local innovation is inevitably generating inequality within cities between low and high skilled groups. While there are clear local gains to innovation, they may also bring about distributional consequences, which policy makers should evaluate carefully before unilaterally supporting initiatives that boosts the technological orientation of the local economy. Local innovation and its role in perpetuating high college wage premiums, particularly in large cities, also have implications across regions with regards to the spatial distribution of skill. Our findings lend support to a role for policies to both ensure the inclusivity of the local economic gains from innovation and to promote a wider diffusion of innovation across cities.

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2.8 Figures and Tables

Figure 2.1: Distribution of College Returns: Simple Mincer

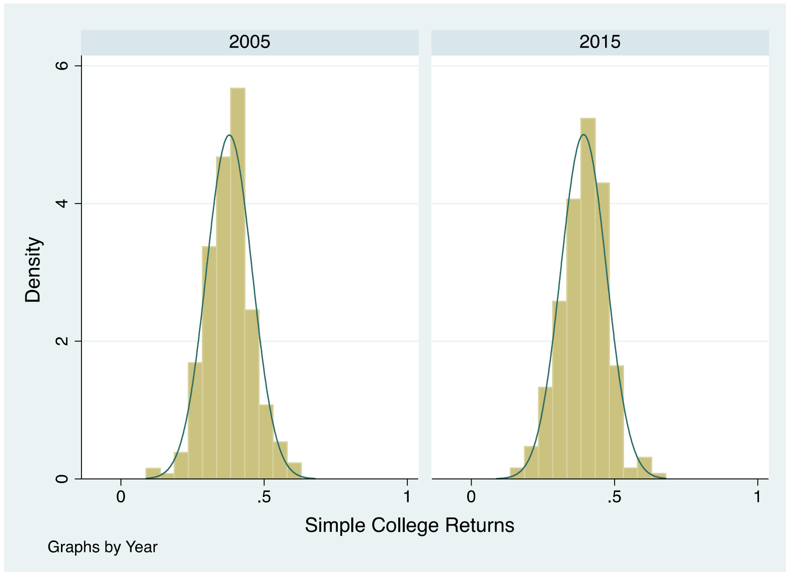

Figure 2.1 graphs the unweighted distribution of the Simple Mincer college returns across metropolitan areas in 2005 and 2015. College returns in the Simple specification is estimated with age, age squared and gender as controls in the 1st stage wage regression.

Figure 2.2: Distribution of College Returns: Extended Mincer

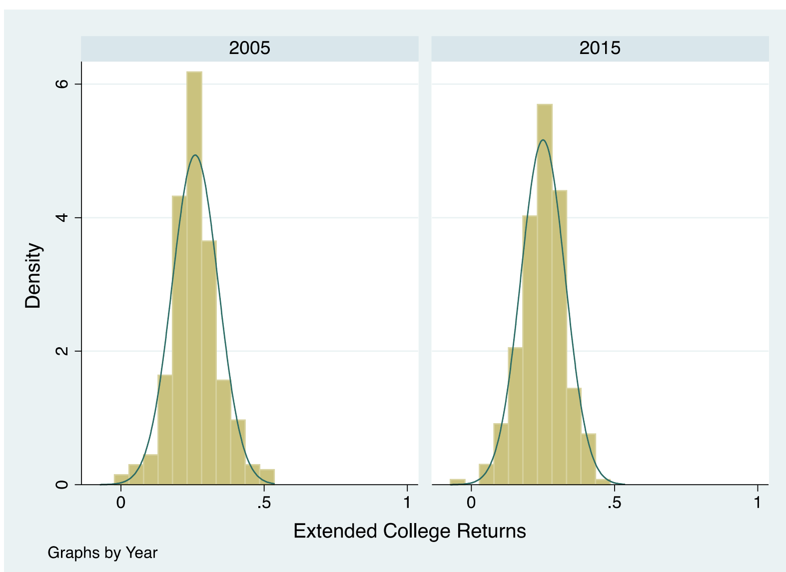

Figure 2.2 graphs the unweighted distribution of the Extended Mincer college returns across metropolitan areas in 2005 and 2015. College returns in the Extended specification is estimated with age, age squared, gender as well as industry, occupation, race, and marital status as controls in the 1st stage wage regression.

Figure 2.3: Correlations Between College Returns and Local Economic Characteristics in 2005: Simple Mincer

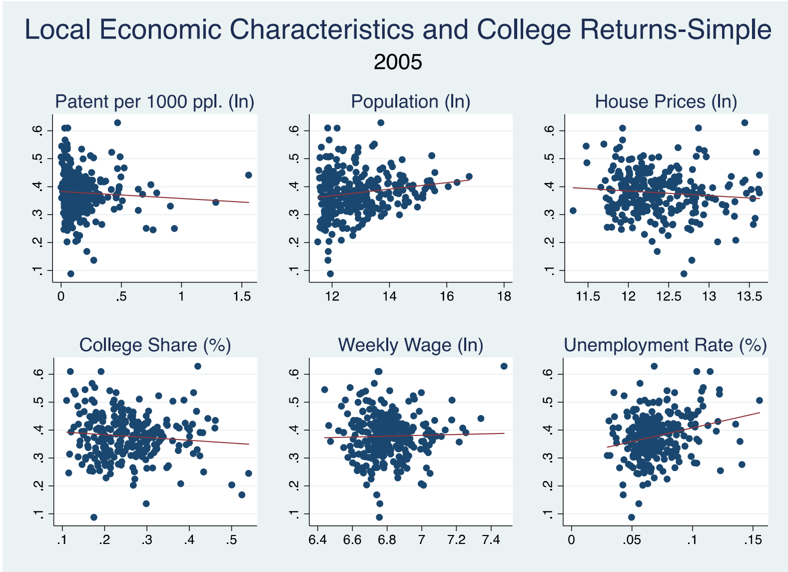

Figure 2.3 plots the correlation between the estimated Simple Mincer specification college returns and the local characteristics of interest in the year 2005. The Simple Mincer college returns are expressed in percentages and the specification is estimated where the controls are age, age squared and gender in the 1st stage wage regression.

Figure 2.4: Correlations Between College Returns and Local Economic Characteristics in 2005: Extended Mincer

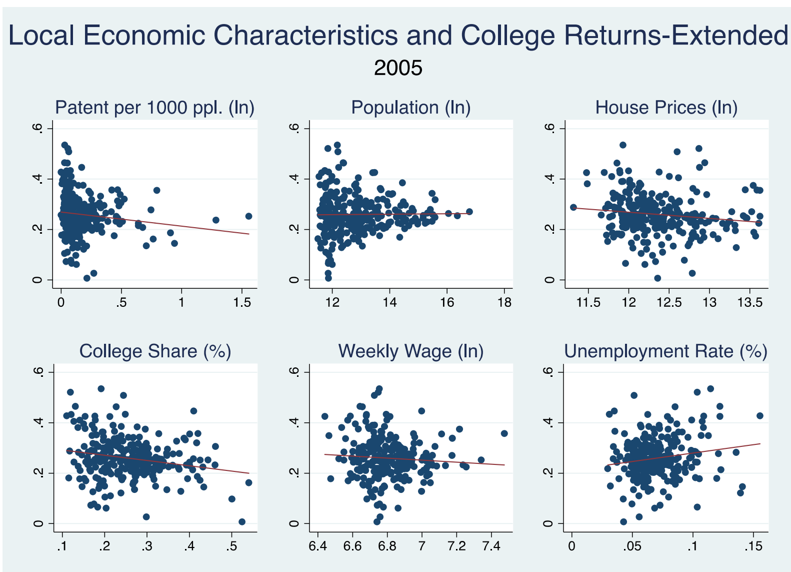

Figure 2.4 plots the correlation between the estimated Extended Mincer specification college returns and all local characteristics of interest in the year 2005. The Extended Mincer college returns are expressed in percentages and the specification is estimated where the controls are age, age squared, gender, industry, occupation, marital status, and race in the 1st stage wage regression.

Figure 2.5: Correlations Between College Returns and Local Economic Characteristics in 2015: Simple Mincer

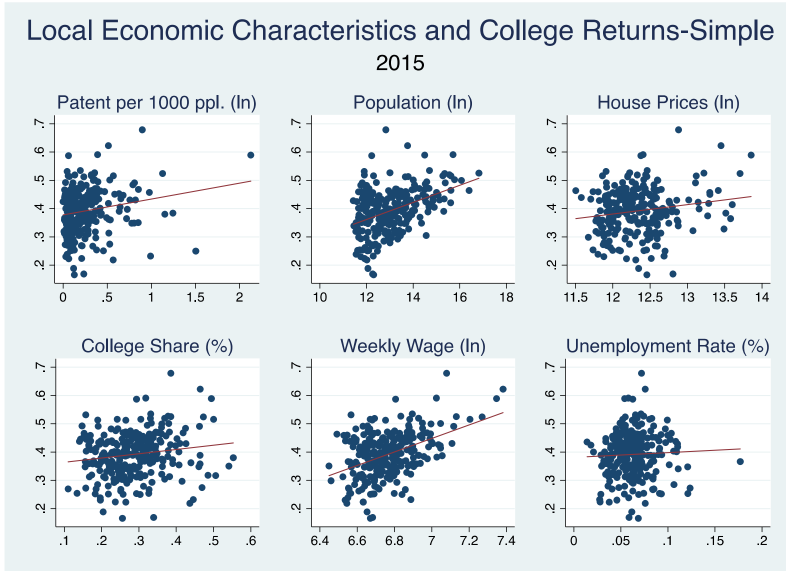

Figure 2.5 plots the correlation between the estimated Simple Mincer specification college returns and the local characteristics of interest in the year 2015. The Simple Mincer college returns are expressed in percentages and the specification is estimated where the controls are age, age squared and gender in the 1st stage wage regression.

Figure 2.6: Correlations Between College Returns and Local Economic Characteristics in 2015: Extended Mincer

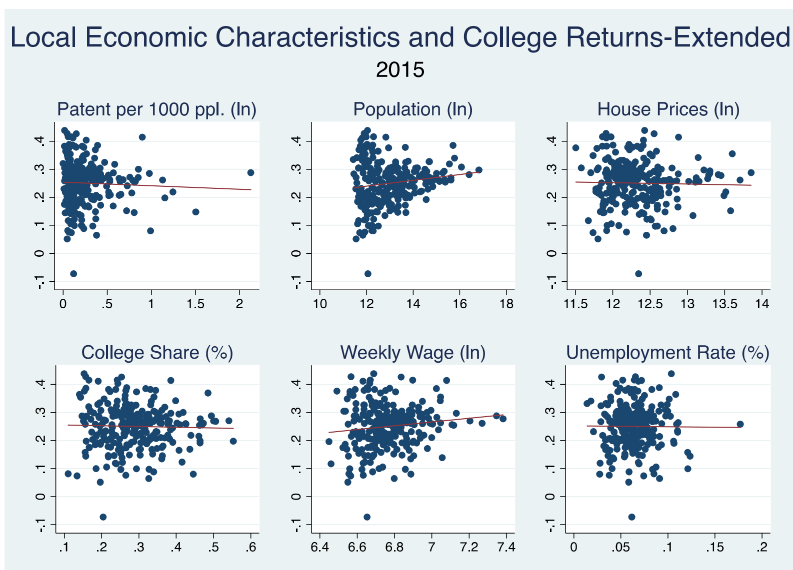

Figure 2.6 plots the correlation between the estimated Extended Mincer specification college returns and the local characteristics of interest in the year 2015. The Extended Mincer college returns are expressed in percentages and the specification is estimated where the controls are age, age squared, gender, industry, occupation, marital status, and race in the 1st stage wage regression.

Figure 2.7: Marginal Effects of Innovation on College Returns by Population Levels: OLS Specification

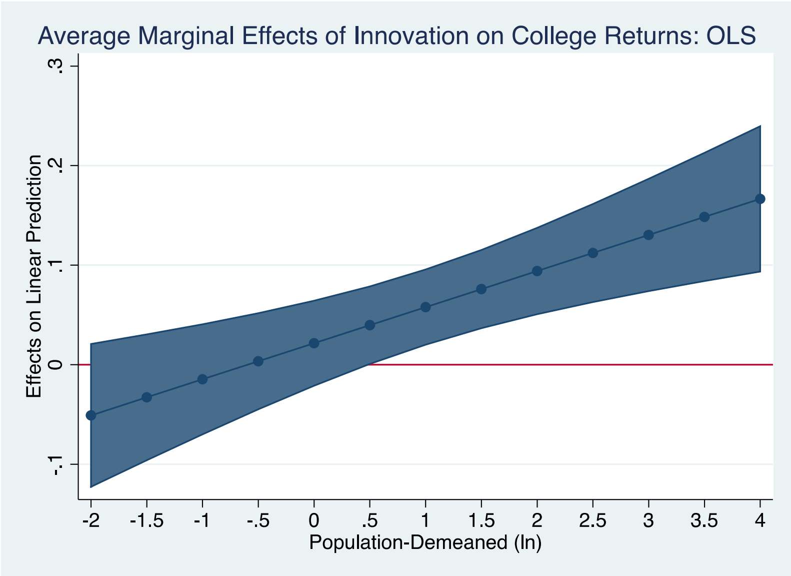

Figure 2.7 plots the marginal effects of innovation on college returns across the city size distribution. These values correspond to the OLS Extended specification estimated in Column 5 of Table 3. The population value is logged transformed and demeaned. A population of zero refers to the city with the mean population value. Shaded areas refer to the 95% confidence interval.

Figure 2.8: Marginal Effects of Innovation on College Returns by Population Levels: IV Specification

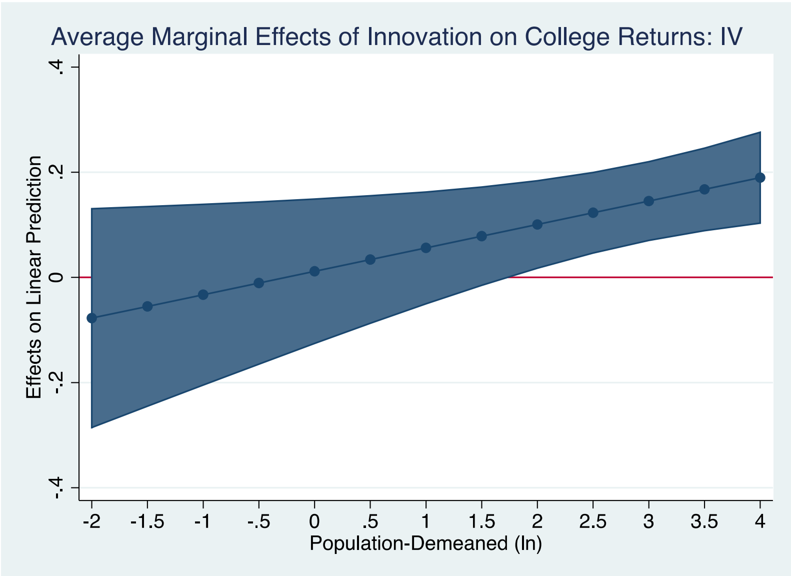

Figure 2.8 plots the marginal effects of innovation on college returns across the city size distribution. These values correspond to the IV Extended specification estimated in Column 6 of Table 3. The population value is logged transformed and demeaned. A population of zero refers to the city with the mean population value. Shaded areas refer to the 95% confidence interval.

Table 2.1: Summary Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
College Returns (%) – Simple Specification	2795	.385	.081	.031	.727
College Returns (%) – Extended Specification	2795	.253	.078	-.075	.578
Number of Patents Issued	2795	377.558	1103.209	0	14894
Log Number of Patents Per Thousand People	2795	.211	.234	0	2.154
Population	2795	946000	1890000	94421	2.02e+07
Log House Price (ln)	2795	12.343	.423	11.222	13.854
Bachelor's degree or higher (%)	2795	.266	.081	.094	.564
Annual Wages ($)	2795	39811.7	6769.652	26046.99	80624.63
Log Annual Wages(ln)	2795	10.021	.165	9.304	10.593
Weekly Wages ($)	2795	872.382	142.082	572.662	1768.797
Log Weekly Wages (ln)	2795	6.759	.151	6.35	7.478
Hourly Wages ($)	2795	22.984	4.238	14.912	100.117
Log Hourly Wages	2795	2.779	.127	2.442	3.278
Unemployment Rate (%)	2795	.081	.029	.014	.207

Table 2.1 reports the descriptive statistics for the MSA characteristics of interest for 265 MSAs between the years 2005 and 2015. The College Returns derived from the Simple Mincer specification is estimated with age, age squared and gender as controls in the 1st stage wage regression. The Extended Mincer specification is estimated with all the controls in the Simple specification as well as controls on industry, occupation, race, and marital status. The variable ‘Bachelor's degree or higher (%)’ refers to the share of the MSA population over the age of 25 with a college degree. Wages and House Prices are expressed in 2015 Dollars.
Source: American Fact Finder and author’s own compilation of ACS data via IPUMS (Ruggles, 2019).

Table 2.2: Top 20 Cities Ranked by Highest College Returns and Composition Features in 2005

Rank	College Returns-Simple	College Returns-Extended	Population	Weekly Wage
1	Bridgeport, CT	Lake Charles, LA	New York, NY	Bridgeport, CT
2	Madera, CA	Madera, CA	Los Angeles, CA	San Jose, CA
3	Lake Charles, LA	Prescott, AZ	Chicago, IL	San Francisco, CA
4	Decatur, AL	Merced, CA	Dallas, TX	Washington, DC
5	El Paso, TX	Waco, TX	Philadelphia, PA	Napa, CA
6	McAllen, TX	Charlottesville, VA	Miami, FL	Trenton, NJ
7	Anniston, AL	Midland, TX	Washington, DC	New York, NY
8	Visalia, CA	Mansfield, OH	Houston, TX	Boston, MA-NH
9	Charlottesville, VA	Hanford, CA	Atlanta, GA	Santa Cruz, CA
10	Waco, TX	El Paso, TX	Detroit, MI	Hartford, CT
11	Merced, CA	McAllen, TX	Boston, MA	Durham, NC
12	Santa Maria, CA	Anniston, AL	San Francisco, CA	Seattle, WA
13	Houston, TX	East Stroudsburg, PA	Phoenix, AZ	Oxnard, CA
14	Yuba City, CA	Gadsden, AL	Riverside, CA	San Diego, CA
15	Hattiesburg, MS	Visalia-Porterville, CA	Seattle-Tacoma, WA	Ann Arbor, MI
16	Trenton, NJ	Jacksonville, NC	Minneapolis, MN	Baltimore, MD
17	Hanford, CA	Decatur, AL	San Diego, CA	Vallejo, CA
18	Lewiston, ME	Tyler, TX	St. Louis, MO	Chicago, IL
19	Huntsville, AL	San Antonio, TX	Baltimore, MD	Anchorage, AK
20	Hickory, NC	La Crosse, WI	Tampa, FL	Santa Rosa, CA

Table 2.2 present the top 20 highest metropolitan area ranked by their respective characteristics in the sample in 2005. Only the name of the central city of the metropolitan area is presented for simplicity.
Source: ACS, American Fact Finder, and own compilation.

Table 2.3: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	OLS	OLS	IV	OLS	IV
Patents Per Thousand People						
[Innovation] (ln)	0.0636***	0.0641***	0.0588**	0.0993*	0.0216	0.0116
	(0.0175)	(0.0181)	(0.0188)	(0.0426)	(0.0206)	(0.0709)
Population (ln)	-0.0193	-0.00600	-0.00556	-0.00448	-0.0114	-0.0153
	(0.0412)	(0.0416)	(0.0437)	(0.0444)	(0.0433)	(0.0452)
House Price [Amenities] (ln)		-0.0329*	-0.0252	-0.0255	-0.0263	-0.0266
		(0.0135)	(0.0153)	(0.0151)	(0.0152)	(0.0152)
College (%)		-0.0752	-0.175	-0.149	-0.203	-0.174
		(0.0951)	(0.106)	(0.106)	(0.108)	(0.110)
Weekly Wage (ln)		0.0553	0.0510	0.0528	0.0529	0.0558
		(0.0394)	(0.0395)	(0.0396)	(0.0393)	(0.0399)
Unemployment Rate (%)		-0.0644	-0.0383	-0.0314	-0.0448	-0.0432
		(0.0965)	(0.1000)	(0.101)	(0.100)	(0.103)
Innovation (ln) x Population (ln)					0.0363***	0.0445*
					(0.00994)	(0.0204)
Observations	2,795	2,795	2,795	2,700	2,795	2,700
R-squared	0.348	0.350	0.364	0.366	0.367	0.033
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage Spec.	Extended	Extended	Extended	Extended	Extended	Extended
Occ Controls	No	No	Yes	Yes	Yes	Yes
Ind Controls	No	No	Yes	Yes	Yes	Yes
Kleibergen-Paap F Statistic	N/A	N/A	N/A	40.39	N/A	7.00
Montiel-Pflueger F-Statistic	N/A	N/A	N/A	874.07	N/A	N/A

Table 2.3 presents the results in the 2nd stage analysis where the dependent variable in all specifications are College Returns expressed in percentages estimated with the Extended specification with age, age squared, gender as well as controls for industry, occupation, marital status, and race in the 1st stage wage regression. Column 4 instruments for patents (innovation) with predicted levels of innovation using a Bartik-style shift-share approach exploiting national level changes in patenting by patent class. The values of each variable used in the interaction specification in Columns 5 and 6 are demeaned. Each specification is probability weighted by the inverse of the standard errors of the college dummy coefficient derived in the 1st stage. All specifications cluster standard errors at the metropolitan area. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.

2.9 Appendix

2.9.1 Appendix A-1

Table A-1: Results [Simple 1st Stage Specification]

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	OLS	OLS	IV	OLS	IV
Patents Per Thousand Worker [Innovation]						
(ln)	0.108***	0.106***	0.0934***	0.203***	0.0339	0.105
	(0.0274)	(0.0276)	(0.0258)	(0.0436)	(0.0229)	(0.0621)
Population (ln)	-0.0358	-0.0297	-0.0310	-0.0236	-0.0394	-0.0444
	(0.0434)	(0.0434)	(0.0452)	(0.0454)	(0.0428)	(0.0438)
House Price [Amenities] (ln)		-0.0259*	-0.0158	-0.0179	-0.0177	-0.0171
		(0.0116)	(0.0127)	(0.0123)	(0.0123)	(0.0121)
College (%)		-0.0322	-0.107	-0.112	-0.152	-0.134
		(0.0840)	(0.0911)	(0.0906)	(0.0925)	(0.0934)
Weekly Wage (ln)		0.0751*	0.0713*	0.0759*	0.0744*	0.0735*
		(0.0332)	(0.0349)	(0.0345)	(0.0346)	(0.0348)
Unemployment (%)		-0.0387	-0.0366	-0.0252	-0.0458	-0.0313
		(0.0930)	(0.0951)	(0.0921)	(0.0955)	(0.0960)
Innovation (ln) x Population (ln)					0.0585***	0.0532**
					(0.0118)	(0.0191)
Observations	2,795	2,795	2,795	2,700	2,795	2,700
R-squared	0.591	0.592	0.602	0.609	0.607	0.050
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage Spec.	Simple	Simple	Simple	Simple	Simple	Simple
Occ Controls	No	No	Yes	Yes	Yes	Yes
Ind Controls	No	No	Yes	Yes	Yes	Yes
Kleibergen-Paap F Statistic	N/A	N/A	N/A	42.32	N/A	7.40
Montiel-Pflueger F-Statistic	N/A	N/A	N/A	874.07	N/A	N/A

Table A-1 presents the results of the 2nd stage analysis where the dependent variable in all specifications are College Returns expressed in percentages estimated with the Simple specification with age, age squared and gender as controls in the 1st stage wage regression. Column 4 instruments for patents (innovation) with predicted levels of innovation using a Bartik-style shift-share approach exploiting national level changes in patenting by patent class. The values of each variable used in the interaction specification in Columns 5 and 6 are demeaned. Each specification is probability weighted by the inverse of the standard errors of the college dummy coefficient in the 1st stage. All specifications cluster standard errors at the metropolitan area. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.

2.9.1 Appendix A-2

Table A-2: Comprehensive Variable Definitions

Variables	Definition
College Residents	Share of residents over 25 with a bachelor's degree or higher.
House Price	Average value of household housing unit
Population	Number of total residents
Patents per 1000 residents	Number of utility patents issued per 1000 residents
Unemployment	Share of unemployed residents
Weekly Wage	Annual reported wage divided by mean weeks worked
Industry Definition	Broad 2003-2007 ACS/PRCS Industry Definitions
Occupation Definition	Broad ACS Occupation Codes (OCC) - 2000-2017

Chapter 3: Robots in the U.K.

3.0 Abstract

The use of robotics automation in the production process is a growing phenomenon across much of the world and is being actively promoted by the U.K. government and industry leaders to strengthen the U.K.'s industrial capabilities despite its job-displacing potential. The U.K. is a special case among developed countries with one of the lowest observed rates of robotics deployment. To evaluate the possible labor market effects of such efforts, this paper studies industrial robotics adoption and its impact on local labor market outcomes in Great Britain between the years 2009 to 2019. Exploiting differences in local exposure to industry-level robotics deployment, we find no impacts on changes in average wages and total employment from increased robot density. Greater robot adoption actually leads to higher employment in industries where robots are most widely used and in occupations whose tasks are complementary to those of robots. Informed by recent evidence, our findings suggest initiatives to boost U.K. automation capabilities, even if adopted at a greater scale, are unlikely to adversely affect labor demand in the U.K. on net and may in fact strengthen the state of U.K. manufacturing jobs. By extending an established empirical approach to the U.K., our results contribute to the broader understanding of the impacts of robotics automation with empirical evidence across multiple country contexts.

3.1 Introduction

There have been extraordinary advancements in robotics automation capabilities in recent decades as robots are now able to perform a wide variety of tasks including welding and packaging with little human intervention. Underpinning this, worldwide robot adoption has risen by more than 150% and the price of robots has halved between the years 1995 and 2005 (Graetz and Michaels, 2018). Advances in such fields have captured our imagination in the economic opportunities they bring but at the same time create unease among those whose jobs they may displace (Brynjolfsson and McAfee, 2014). In a survey carried out by Sky News, 30 percent of British respondents believe their job could be replaced by automation technologies in the next 20 years.[21] Even noted entrepreneur Bill Gates has proposed a tax on robots as the robots that replace people's jobs 'do not pay income taxes.'[22]

We set out to answer the question on whether automation advances are actually leading to worse labor market outcomes for workers in the U.K.[23] in the very recent era between 2009 to 2019. The U.K. is an interesting context where it is among the countries with the lowest robot density across developed nations but stakeholders in industry and policy making circles increasingly recognize the importance for a greater role of automation technologies in the economy. A greater rollout of such technologies, as some argue, could be a panacea for the problems plaguing the U.K. economy such as the poor observed rates of productivity growth in manufacturing and other sectors. While the benefits to greater automation are widely highlighted, it raises important issues regarding the labor market consequences of a wider embrace of automation technologies. Hence, a study focused specifically on the U.K. is warranted to examine whether recent initiatives to embrace automation technologies would have unintended labor market ramifications domestically. Studying such developments in a low-automation country such as the U.K. would also contribute to a better understanding of the general effects from automation. Past studies have explored robotics automation developments in highly automized economies such as the U.S. and Germany (Acemoglu and Restrepo, 2020; Dauth et al., 2021), with diverging conclusions[24] on how it affects overall labor demand. As the contrasting findings from past studies can be, in part, explained by their market and institutional characteristics given the differences between a very liberal market economy (USA) and a coordinated market economy (Germany), it becomes important to examine these forces in a different institutional context, which sits in-between (the UK is a liberal market economy, but with more 'European' characteristics than the USA). An extension of their approach to a new context can help determine which state of the world better characterizes how workers are affected as a result of a more automated economy more broadly.

In this paper, we follow the empirical strategy of Acemoglu and Restrepo (2020), and subsequently utilized by Dauth et al. (2021), and adopt a shift-share approach to infer robot exposure at the sub-national scale, in order to examine the issue, exploiting variations at the local

[21] https://interactive.news.sky.com/Robots_Tabs_FULL.pdf
[22] https://www.ft.com/content/d04a89c2-f6c8-11e6-9516-2d969e0d3b65
[23] We only study developments in Great Britain due to data limitations but our findings apply more broadly to the U.K. as a whole.
[24] Acemoglu and Restrepo (2020) find sharp negative effects on net labor demand in the U.S. while Dauth et al. (2020) find negligible net employment effects in Germany.

labor market level in Great Britain. As the robot adoption patterns across firms and industries are not random and are endogenous to local and industry-specific conditions, we also complement the analysis with instrumental variable specifications utilizing the robot adoption rates, at the sectoral level, of other developed nations, yielding plausibly causal interpretation. On net, we find little effects to median wages and total employment from greater robot density. However, there are important sectoral and occupational differences. Our results show that greater robot exposure has actually led to gains in manufacturing employment, consistent with evidence of productivity gains from robot adoption; while it has also led to employment gains (losses) for non-routine (routine) occupations. These findings are consistent with a dynamic interpretation of automation, with *both* task creation and displacement occurring simultaneously.

Our paper makes two distinct contributions; first we advance the discourse on the empirics of robotics automation, adding to the international literature on the topic; second, our results help to inform possible policy choices of the U.K.'s technology and industrial policies. By extending an established empirical approach, we provide additional evidence on the within-country labor market implications of robotics automation. Our results in the U.K. better align with those found by Dauth et al. (2021), Adachi et al., (2020) and Cali and Presidente (2022) of the German, Japanese, and Indonesian automation experiences respectively, countries at opposing ends of the robot adoption distribution. Taken together, our results and the findings of past studies suggest that advances in automation in general does not imply net reductions in labor demand and can in fact lead to gains in employment in directly affected sectors. Our findings also help inform U.K. policy. Despite the possibility for automation technologies to displace employment, the evidence we provide suggests that initiatives to boost automation capabilities would not necessarily lead to negative labor market implications and, importantly, if deployed appropriately they may help contribute to the objectives set out in the country's recent 'Leveling Up' agenda (HM Government, 2022) and other industrial policy objectives. Given, however, that some occupations are more prone to displacement than others, such deployment will have to be combined, it seems, with targeted active labor market policies to assist at-risk workers during times of technological change.

The next section discusses the theoretical considerations of automation and reviews the empirical literature of industrial robots and labor market outcomes. Section 3.3 assesses the relevance of industrial robotics in the U.K. context. Sections 3.4 and 3.5 introduce the data and methodology and present initial descriptive evidence. We present our main findings in Section 3.6 and discuss them in Section 3.7. Finally, Section 3.8 concludes.

3.2 Labor Market Implications of Robotization

The theoretical and empirical aspects of automation and technological change and their impacts to labor demand have been extensively studied and reviewed (Berman et al., 1998; Acemoglu and Autor, 2011; Goos et al., 2014; Acemoglu and Restrepo, 2018). In a static world where automation is purely thought of as a labor-saving and task-displacing technology, automation is predicted to reduce labor demand, with lowered wages and employment as likely outcomes (Acemoglu and Restrepo, 2018). In a dynamic setting, automation itself also leads to the creation of new tasks in the economy, generating higher labor demand in other domains (Ibid). Hence the aggregate implications of automation on labor demand depend crucially on the relative strengths of its displacement potential and its propensity for new task creation. Furthermore, the labor market effects of automation at the aggregate level are also conditional on the speed and extent of labor reallocation across industries (Autor and Salomons, 2018). Industries more exposed to labor-displacing automation technologies reduce labor demand and shed employment but displaced workers are eventually redirected towards industries with a higher labor share content, with ambiguous long-run aggregate implications (Ibid). Such theoretical exercises lead to the prediction that robotization, a technology-specific form of automation, could lead to lower labor demand in the short run but this relationship also hinges on new tasks creation from automation and industry reallocation if robotics automation affects industries heterogeneously.

Graetz and Michaels (2018) were among the first to empirically examine automation in the form of robots specifically. In their study, they show that average wages rise as a result of robotics automation though the relative share of low-skilled workers in employment is reduced, as they are possibly displaced and replaced by robots. In an approach more akin to ours, Acemoglu and Restrepo (2020) find large and consequential negative effects to labor demand in the U.S. as a result of robotics automation. They estimate that the introduction of one new robot replaces 3.3 jobs and their back-of-the envelope calculations suggest that up to 500,000 jobs were displaced between the years 1990 to 2007. By contrast, Dauth et al. (2021), using the same approach, find no overall effects to wages or employment in Germany. They do, however, document significant heterogeneities in how workers are affected across occupation and industry groups. Manufacturing employment were displaced but much of the decline was offset by increases in non-manufacturing employment. Meanwhile, those working in non-routine occupations with skills that complement the comparative advantages of robots such as managerial and research-oriented professions experience gains in employment. Conversely, the reverse is true for routine-intense occupations where increased robotization was found to have displaced employment in such domains (Ibid). Such findings are also affirmed by de Vries et al. (2020), that find significant displacement effects from industry-level robotization particularly for routine, manual task-intensive employment across industries in developed economies. Elsewhere, others, using the same industrial robotics data, have also studied robot penetration in additional country contexts using the local labor market approach. In Japan, a developed-economy setting and the most robot-dense country in the world, the authors (Adachi et al., 2020) find strong complementary effects between robots and employment through productivity channels as an increase in one robot per thousand worker raises employment by 2.2%. This, the authors argue, occur as Japanese manufacturing firms, export-oriented in nature, cater extensively to overseas markets hence robotization, which enhances manufacturing productivity, induces sizeable scale effects, which more than offsets any potential displacement patterns. In Indonesia, a developing-economy context with very low rates of robot penetration, Cali and Presidente (2022) also observe significant positive productivity and employment effects through robotization. This, they contend, is a result of diminishing productivity returns to automation; robotization brings out large productivity effects at low rates of robot adoption though such effects may diminish as robot uptake creeps up. Given the different empirical findings of many of these studies, all of which employ the local labor market approach, there remains little consensus as the empirical impacts of robotization on labor market outcomes varies across in specific countries and contexts. To evaluate the impacts of automation specific to the U.K., a study devoted to the context, such as ours, is necessary. The next section introduces and characterizes the U.K. context.

3.3 The U.K. Context

The U.K. is an outlier among developed nations in the pace of robotization with one of the lowest rates of robot penetration. As shown in Panel A of Figure 3.1, the U.K. has the lowest economy-wide levels of robot penetration across major developed economies with one-tenth and one-third of the number of employment-adjusted robots in operation compared to Germany and the U.S. respectively. The U.K. still lags far behind its peers even when robot adoption levels are viewed in relation to manufacturing employment as shown in Panel B of Figure 3.1, suggesting that low robot uptake is not necessarily due to industry composition.[25] Robot uptake in the U.K. could be low for a variety of reasons including the fact that it is not a manufacturing-intensive economy as compared to Germany or that it does not have the fiscal incentives and tax structures that promote investments in automation such as in the U.S. (Acemoglu et al., 2020). Nevertheless, the U.K. may have much to gain from a more widespread use of robots in the economy. In recent years, the U.K. economy has experienced poor rates of productivity growth since the financial crisis, with the phenomenon especially acute in the manufacturing sector (MGI, 2018; Tenreyo, 2019). Hence a more widespread adoption of robotics technology could be a pathway to raise the productivity potential of U.K. industries and the economy as a whole. The possibility that industrial robots has the capacity to transform the state of U.K. manufacturing has not gone unnoticed. The U.K. parliament commissioned a report calling on the government to do more to support British industries to increase their physical automation capabilities including increasing tax incentives for robot adoption (House of Commons, 2019) Similarly, the Made Smart Review, an industry-led report commissioned by the government, highlights that catching up with its international competitors in the use of industrial robots as part of a larger industrial digitalization plan could boost the output of U.K. manufacturing by more than £455 Billion. (BEIS, 2017). Indeed the government has made efforts to support such initiatives including pledging up to half a billion pounds in its commitment to support the Robotics and Autonomous Systems (RAS) network, a forum bringing together academic expertise in robotics innovation and industry partnerships (RAS, 2014). While there is consensus among U.K. stakeholders on the possible benefits of robotics technology as discussed earlier, the potential costs stemming from possible job losses or wage declines specific to the U.K. are less clear given the discussion earlier. Our study seeks to fill this gap and, in this way, offer evaluatory evidence to support policy-making initiatives specific to the UK.[26]

[25] One possible explanation of low robot adoption in the U.K. could be its small share of the economy devoted to manufacturing, a sector where nearly all industrial robots are deployed. However, this hypothesis cannot explain the UK's low adoption rates entirely as they are still more than twice as low as other developed economies when robot values are normalized by manufacturing employment instead.

[26] We do not attempt to answer whether such initiatives meant to promote greater robotization would be successful but rather to quantify its possible effects to labor markets if they are based on recent UK robotization trends.

3.4 Data and Approach

Data on industrial robots is sourced from the International Federation of Robots (IFR).[27] The IFR is a professional non-profit organization whose mission is to promote, strengthen and protect the robotics industry worldwide. Robot installation and stock data is available at the country-industry level and comes from an annual survey of robot suppliers covering more than 70 countries and territories.[28] Our precise measure for robotics adoption is the count number of robots installed and in operational stock. Such data are reported for only a subset of predominantly manufacturing industries where there is meaningful adoption rates to be separately detailed. Data on employment by industry in the U.K. originates from the Business Register and Employment Survey (BRES), an annual government survey of firms. There exist two different vintages of BRES: a full version of BRES available from 2015 to 2019 and a version of BRES with a reduced sample of firms available from 2009 to 2015. The two vintages are connected through a 'splicing' process based on their year of overlap, recovering a time-consistent measure of employment at the industry-local labor market and local level between 2009 to 2019. More details of the 'splicing' methodology can be found in Appendix A-3. Data on wages originate from the Annual Survey of Hours and Earnings (ASHE). This is a 1% sample of employee jobs obtained from HMRC, the U.K. tax collection agency. Employment breakdowns by occupation and other local labor market characteristics are sourced from the Annual Population Survey (APS) and the Labour Force Survey (LFS) obtained from the NOMIS web portal of the Office of National Statistics (ONS).

We study the impacts of robotics automation focusing our attention at the subnational level exploiting variation across regions. Regions can be an ideal setting to study automation developments as they can resemble individual labor markets, with local industry make-ups that vary in their exposure to technological change. An analysis at the region or local level can also capture equilibrium labor market adjustments resulting from the arrival of automation technologies including potential displacement, spillover and/or reallocation effects.[29] As we do not observe robot uptake locally, we use the robot adoption rates at the industry level and local industry composition to recover an estimated robot exposure measure at the local labor market level using

[27] A robot is officially defined as an 'automatically controllable, re-programmable, and multipurpose machine that do not need a human operator and can be programmed to perform several manual tasks' (IFR, 2020).
[28] This survey covers more than 90% of all robot installations worldwide for any given year.
[29] In addition to being ideal setting to analyze the labor market effects of technological shocks (e.g. Acemoglu and Restrepo, 2020; Acemoglu et al., 2022), the use of local labor markets and their differential exposure to economy-wide trends have also been applied in other contexts to study different types of labor market adjustments such as trade shocks as an example (e.g. Autor et al., 2013).

a shift-share approach, following Acemoglu and Restrepo (2020). This is done by interacting the change in robot stock at the industry level ‘j’, standardized by the industry size (employment level) of the initial year ‘b’, by the employment share of the same industry in local labor market ‘l’ during the initial year ‘b’ – as shown in Equation 1.[30]

$$\Delta\widehat{Robots}_l = \sum_{j=1}^{J}\left(\frac{emp_{jlb}}{emp_{lb}} X \frac{\Delta robots_j}{emp_{jb}}\right) \quad j == 17 \qquad [1]$$

This is then summed across all industry ‘j’s to form an estimated robot exposure measured at the local labor market level expressed in changes between the years 2009 and 2019. Local labor markets with high (low) rates of estimated robot exposure are those with high (low) shares of employment in industry ‘j’s and a high (low) ratio of robots relative to employment in industries ‘j’s. Our preferred subnational unit of analysis are Travel to Work Areas (TTWA) as it is the most commonly used commuting-based measure of local labor markets in the U.K. (Lee and Clarke, 2019). TTWAs are drawn so that at least 75% of the area’s workforce live in the area.[31] We recover data at the local authority district (LAD) level and aggregate values up to TTWAs using a postcode-based crosswalk from Gutierrez-Posada et al. (2022). This allows us to recover data on 212 TTWAs or local labor markets located predominantly in Great Britain.[32] Our robot exposure measure, as shown in Equation 1, is estimated in changes-in robots per thousand worker, for consistency with past studies. Robot installation and stock data can be recovered for 17 industries, reported in ISIC rev. 4 classifications, of varying granularities including 14 manufacturing and 3 non-manufacturing sectors. Table A-1 in Appendix A-4 shows the detailed list of industries used in the analysis and their reported granularities. Empirically, we use a differences specification shown in Equation 2 to investigate the relationship between robotics automation and local labor market outcomes.

$$\Delta Y_l = \Delta\widehat{Robots}_l + \Delta\widehat{ICT}_l + Controls_{lb} + \varepsilon_l \qquad [2]$$

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[30] While firms or establishments within industries across local labor markets may differ in their actual level of robotics adoption, our measure should still appropriately capture automation exposure manifested in local labor markets as it captures general industry-wide trends in robotics adoption.

[31] TTWAs must also have an economically active population of at least 3,500. Also, for TTWAs with a working population in excess of 25,000, self-containment rates as low as 66.7% are accepted as part of a limited trade-off between workforce size and levels of self-containment.

[32] While our study is based in the U.K., the local labor market we examine are predominantly located in Great Britain, without coverage in Northern Ireland.

The change in outcome variable 'Y' in local labor market 'l' between 2009 and 2019 is regressed against the main explanatory variable of interest, the robot exposure measure '$\Delta\widehat{Robots}_l$', concurrent changes in another distinct form of technology '$\Delta\widehat{ICT}_l$'[33], and a battery of control measures in the base year 'b'. Inspired by Dauth et al. (2021), our control set includes the industry shares of 9 broad industry groups, the shares of each major education group[34], and the shares of workers over 50, female workers, and foreign workers as well as a fixed effect for each nation in Great Britain.[35] Standard errors are clustered at the local labor market level.

A potential problem of endogeneity remains as U.K. industrial robot uptake, however, is not randomly assigned and is likely related to the conditions and production complementarities of U.K. firms and industries. It is likely that the domestic firms that stand the most to benefit from robotics automation are more likely to procure them; this could lead to a selection bias in the adoption of robots, possibly upwardly biasing the results in a naïve OLS setting. To overcome such concerns, we additionally deploy an instrumental variable approach adopted from Acemoglu and Restrepo (2020). The robot exposure measure, calculated at the local labor market level, '$\Delta\widehat{Robots}_l$', is instrumented with an alternative exposure measure, shown in Equation 3, estimated using the robot adoption of the same industries in other high-income economies instead.

$$\Delta IV\widehat{Robots}_l = \sum_{j=1}^{J}\left(\frac{emp_{jlb}}{emp_{lb}} X \frac{\Delta robots_{cj}}{emp_{jb}}\right) \quad j == 17 \qquad [3]$$

The instrument, '$\Delta IVRobots_l$', is analogous to the exposure measure in Equation 1 except the term, '$\Delta robots_{cj}$', where we utilize the national level trends in robotization in the same time period and industries 'j' of other high-income countries 'c'.[36] This instrument, which exploits global trends in robotization, eliminates endogeneity concerns arising from U.K.-specific considerations in the choice to adopt robots in the production process. We utilize this instrumental variable strategy in two approaches. In the first approach, the instrument is calculated for each

[33] ICT technology is measured as the change in gross fixed capital formation in computing and communications equipment. This is measured at the industry level and we recover a local measure of exposure to ICT technology expressed in pounds per worker using the same shift-share approach outlined in Equation 1.
[34] We use the National Vocational Qualifications (NVQ) framework to classify skill groups with 7 distinct categories.
[35] Local labor markets that cross national boundaries are coded separately and is considered its own 'nation' for the purposes of the fixed effects specification.
[36] We use the robot adoption of the U.S., Germany, France, and Italy for the construction of our instrument.

country using Equation 3 and deployed in the specification as separate instruments. In the second approach, we aggregate the change in robot stock in the selected high-income countries treating it as one country and estimate the instrumental variable specification with one single regressor following Dauth et al. (2021).[37]

3.5 Descriptive Statistics

We start by providing descriptive details outlining the nature of industrial robot adoption in the U.K. and Great Britain across industries and local labor markets. As illustrated in Panels A and B of Figure 3.1, the U.K. nationally has installed a much smaller number of total robots relative to employment when compared with its international peers. Figure 3.2 depicts the change in employment-adjusted robot penetration at the national level across industries between 2009 to 2019. Net robot installations in this period are most pronounced in manufacturing, particularly in the manufacturing of automobiles. The skewness of robotics adoption towards manufacturing, and more specifically in automobile manufacturing, has also been documented in other countries including Germany and the U.S. (Acemoglu and Restrepo, 2020; Dauth et al., 2021). For non-manufacturing industries where data is available such as mining and construction, there was little or no net change in robot stock.

[Insert Figure 3.2]

Figure 3.3 displays the top ten local labor markets in Great Britain with the highest exposure to robotics automation measured using the approach outlined in Equation 1 expressed in changes.[38] Not surprisingly, high-exposure local labor markets are strongly associated with the presence of local automotive manufacturing operations corroborating the national industry-level patterns in Figure 3.2.[39] To probe the geographical dimensions of robotics uptake in Great Britain, Figure 3.4 displays the spatial distribution of changes in robot exposure across labor markets by

[37] We deploy the instrumental variable strategy separately to ensure the effects we recover are robust to number of countries (and instruments) we choose to induce variation in our IV choice set.

[38] This essentially shows the local labor markets with highest concentrations of robot-adopting industries.

[39] For instance, the top local labor market with the highest estimated change in robot exposure is Sunderland, home to global automobile manufacturer Nissan. Elsewhere, the labor markets that house the manufacturing plants of carmakers Honda [Swindon], Ford [Bridgend], Bentley [Crewe], and Land Rover [Birmingham] are also represented in the figure.

each quartile of robot exposure.[40] Local labor markets with the highest increases in robot exposure in Great Britain are primarily in England. A number of local labor markets in the top quartile of robot exposure increases are located in the Midlands, a region traditionally associated with a strong manufacturing presence, though highly automized labor markets appear to be dispersed elsewhere across England. Perhaps surprisingly, regions in Great Britain with large automation exposure shocks during this period are geographically concentrated in the East of England and in the South East. While not historically known for manufacturing capabilities, large automotive corporations such as Caterpillar, Vauxhall Motors and McLaren Automotive, among others do have large operations located in these regions.

[Insert Figures 3.3 and 3.4]

Table 3.1 presents the summary statistics of the main outcome and explanatory variables of interests along with the associated control measures in our specification. Our main explanatory variable, robot exposure, is measured in units of robots per thousand worker and expressed in changes. For outcomes of interest, employment and wages are measured in percentage change and the change in log weekly values respectively. To preview our empirical results and to motivate our findings, we present descriptive evidence on the relationship between changes in the estimated local robot exposure and changes in employment and wages between the years 2009 and 2019 as shown in scatterplots in Figures 3.5 and 3.6 respectively. Growth in robotics automation exposure through increases in robot stock is actually associated with increases in employment while there appears to be no correlation between changes in wages and robot exposure. The correlational observations presented here indicate positive associations between robotics automation and employment outcomes. More needs to be done to tease out the actual labor market effects in Great Britain and the U.K. empirically.

[Insert Figures 3.5 and 3.6 here]

[40] Some local labor markets in Scotland are excluded because of a lack of information in the crosswalk used in the aggregation from Local Authority Districts to Travel to Work Areas.

3.6 Results

Table 3.2 shows the results from empirical specifications examining the impact of changes in robot exposure on total employment changes between 2009 to 2019. Both the OLS and the IV specifications are shown in Columns 1 and Columns 2-3 respectively, with the latter yielding a causal interpretation. Column 2 shows the IV specification with countries as separate instruments in the first stage while Column 3 shows the IV construction where the robot adoption of all other chosen countries are summed to form one single instrument. Increases in robot exposure are positively associated with increases in employment across all specifications though the results are statistically insignificant. Table 3.3 reports the results for changes in robot exposure on median weekly wage at the local labor market-demographic cell level.[41] The outcome of interest here is expressed in log changes. The OLS and IV results in Table 3.3 are presented in the same format and order as Table 3.2. Akin to the findings for employment, Table 3.3 also suggest positive but negligible wage gains from automation advances in the same period. These empirical results are consistent with the descriptive evidence presented earlier of a mild but positive association between recent automation advances and observed changes in labor market outcomes. High reported values of the Kleibergen-Paap F statistic across the IV specifications in both Tables 3.2 and 3.3 demonstrate the suitability of the instrument in our context.[42] The empirical results for both employment and wage are consistent with the findings documented in Dauth et al. (2021), which also do not find any meaningful changes in net employment and wages in Germany. The results are indicative that automation, in the form of robots, is not necessarily the suspected job-displacing form of technological change in the U.K. that members of the British public have feared. Beyond this aggregate picture, however, specific industries and occupations may be differentially affected given that robots, as a form of automation, are substitutes as well as complements of certain tasks in the labor market. We now turn to analyzing robotics automation's possible differential effects across occupation and industry groups.

[41] The unit of analysis for analyzing changes in wages is at the local labor market-demographic cell level following Acemoglu and Restrepo (2020) with four separate cells: male full-time workers, female full-time workers, male part-time workers, and female part-time workers. This is done to account for changing observable characteristics of the labor market at the local level that affect wages. While the demographic cell breakdown we deploy is less granular than past work, fluctuations in local wages arising from changing labor market demographics are arguably less of a concern given our shorter time period of analysis.

[42] While the reported F-Statistics in Tables 2 and 3 can be viewed as high, they are similar in magnitude to those reported in the literature (e.g. Dauth et al., 2022).

Table 3.4 focuses on the relationship between changes in robot exposure and employment growth across industries distinguishing between manufacturing and non-manufacturing sectors. This distinction is meaningful as the manufacturing sector has been the most enthusiastic adopters of robots as shown earlier. Columns 1-3 display the results for manufacturing employment while Columns 4-6 show the same set of results for non-manufacturing industries. We observe, from both the OLS and IV results, that increased robotization has a strong positive effect on manufacturing employment growth while no effects are reported for non-manufacturing sectors. Given that robot installations in the U.K. in manufacturing sectors have been increasing during this period, manufacturing employment may have actually increased as a result of greater automation within the sector[43], which is contrary to the expectations of large labor displacement occurring. An increase in employment could be, in part, driven by a productivity effect as a result of adopting automation technologies (e.g. Gratz and Michaels, 2018). The increase in manufacturing employment from robotization in the U.K. can also be rationalized with the automation experiences in Indonesia (Cali and Presidente, 2022) with strong productivity benefits found from robotization, leading to greater manufacturing labor demand, at low rates of robot adoption, though such effects may dissipate at greater levels of automation given diminishing productivity returns. In light of such findings, it is possible that the observed increases in manufacturing employment from robotization in the U.K., with unusually low rates of robot adoption, are driven by a productivity effect though such mechanisms could fade once the U.K. catches up with its developed-economy peers in robot penetration. Another related mechanism that could be taking place is that automation technologies can generate higher labor demand by enhancing the ability for individual manufacturers and firms in developed economies to compete internationally (Adachi et al., 2020; Aghion et al., 2021). In the U.K. specifically, there is evidence that greater adoption of automation technologies, in the context of rising import competition from China, is positively associated with higher employment both at the firm and local labor market level through high rates of firm survival (Webb and Chandler, 2022) though more work may be needed to better understand these mechanisms at work. Finally, in contrast to Dauth et al. (2021), we find no evidence that manufacturing employment was reallocated to non-manufacturing sectors across local labor markets, which is perhaps not a surprise as we find no displacement effects to manufacturing employment to begin with.

[43] Or have not decreased as severely.

Occupations with a high degree of routine intensity are traditionally those most susceptible to automation and technological change while non-routine occupations contain tasks considered to be harder to automate with existing technologies (Autor and Dorn, 2013). Robotics automation have also been empirically shown to exert differential displacement effects to jobs based on routine intensity (de Vries et al., 2020; Dauth et al., 2021). To further probe the heterogenous impacts of increased robotization across workers in the U.K., we assess the differential effects on employment growth across occupations distinguishing between routine and non-routine occupations as presented in Table 3.5.[44] Columns 1 through 3 and Columns 4 through 6 display the results where the outcome variables are the percentage change in routine and non-routine employment respectively. For routine occupations, advances in robotics automation are associated with declines in employment, which is consistent with initial expectations of the kinds of tasks robots replace though the estimates are not particularly strong or stable. By contrast, employment growth occurs in non-routine occupations when local labor markets experience robotics automation shocks. The differential effects of automation on employment across occupational lines by task content (routine versus non-routine) is consistent with a dynamic interpretation of automation with both displacement *and* reallocation taking place. The arrival of robotics technology likely displaces some jobs in parts of the economy with task content where it holds a comparative advantage in and simultaneously generates growth in occupations that likely complement robots in the production process. Our results, for both manufacturing/non-manufacturing and for routine/non-routine employment, are also robust to the use of an alternative measure of employment – the change in the employment to population ratio[45] – and measure of local automation exposure – the change in robotics exposure per 1000 manufacturing worker[46] – as shown in Table A-2 of Appendix A-6 and Table A-3 of Appendix A-7 respectively.

[44] Details of the occupation routine classification are elaborated in Appendix A-5.

[45] The main results in Tables 3.4 and 3.5 where the dependent outcome of interest is the percent change in employment in local labor markets may be sensitive to the initial size of the local labor market. Hence an outcome variable, e.g. the change in the employment to population ratio, that is normalized by population is less susceptible to size-driven employment fluctuations.

[46] As much of robotics uptake across industries are mainly felt in manufacturing, this measure is seen as a more direct measure of robotics exposure at the local level.

3.7 Discussion

Our findings in Great Britain and the U.K. most closely resemble those found by Cali and Presidente (2022) and Dauth et al. (2021) with positive effects to manufacturing employment and task displacement and reallocation of jobs with high routine intensity. The fact that we observe similar empirical outcomes in the most *and* least robot-dense economies (e.g. Germany, Japan and the U.K.) using the same approach adds credence to the idea that advances in automation technologies do not create long and persistent declines in labor demand and may in fact even raise labor demand under certain conditions. While Acemoglu and Restrepo (2020) find largely negative consequences from robotization in the U.S., their findings are in a context where, as some of the same authors have shown in a separate study, the tax code has persistently and excessively favored capital spending on technologies over employing labor. Acemoglu et al. (2020) have argued that the effective tax on labor is up to two times greater than the rate of the tax on corporate equipment and software spending, capital investments in areas traditionally associated with automation technologies. The difference in taxes on labor and capital spending on areas associated with automation technologies have only grown wider since the 2000s. While the results from Acemoglu and Restrepo (2020) on robots and labor market outcomes raises important issues on the consequences of automation technologies, their findings may not be indicative of the general experiences of automation in most countries given such unique institutional peculiarities. By expanding on an existing empirical approach, we contribute to the literature and our results side with the wider existing empirical works of a more nuanced, dynamic, and somewhat positive interpretation of the effects to labor demand from automation. Robotics advancements does not depress net employment or wages though its effects may affect various industries and occupations differently given the productivity effects of the adoption of such technologies and the dynamics of task creation and displacement.

Given that no previous study has examined the employment effects of robots in the UK, our results also have the added contribution of informing the state of the U.K.'s industrial policies. Calls for a wider adoption of automation technologies across multiple stakeholders may be drowned out by fears of large-scale displacement effects from the general public. Our results, using up-to-date data across local labor markets in Great Britain, show that such fears are likely unfounded and that enhancing automation advancements along the lines industry and policy stakeholders have suggested would unlikely lead to severe labor market implications. In fact, our results suggest the state of manufacturing jobs in the U.K. could actually be strengthened from further robotization if deployed appropriately, particularly in moderate proportions and if it helps U.K. manufacturers better compete globally. As automation would inevitably lead to some degree of task displacement, our findings do suggest that certain segments of workers could be adversely affected, particularly among those in routine occupations. This suggests scope for active labor market policies to support worker retraining and reskilling initiatives, to be rolled out simultaneously as part of a wider industrial strategy, to counteract the possible displacement effects of automation among a specific subset of the workforce.

3.8 Conclusion

We study the contemporaneous effects of recent advances in industrial robots on labor market outcomes in the U.K. given the widespread interest in the area from members of the public to industry stakeholders keen to upgrade the state of U.K. manufacturing. Our study, exploiting changes in local labor market outcomes in Great Britain from the years 2009 to 2019, indicates that automation advances in recent years have little net effects to labor markets as we document negligible impacts to median wages and total employment from increased robot use in the economy. We document increases of employment in manufacturing industries, the sectors in which robots are most widely used, consistent with a strong productivity-inducing effect from robotization. There is evidence of displacement, as indicated from the documented decline in routine occupations, from increased robotization of the economy but automation advances also generate employment growth in other non-routine occupations quite likely by creating new tasks in the labor market. Our findings on the labor market effects of automation in the U.K. adds to the wider empirical understanding of the impacts of automation as well as contribute to the policy debates surrounding the future of the U.K.'s industrial strategy.

3.9 References

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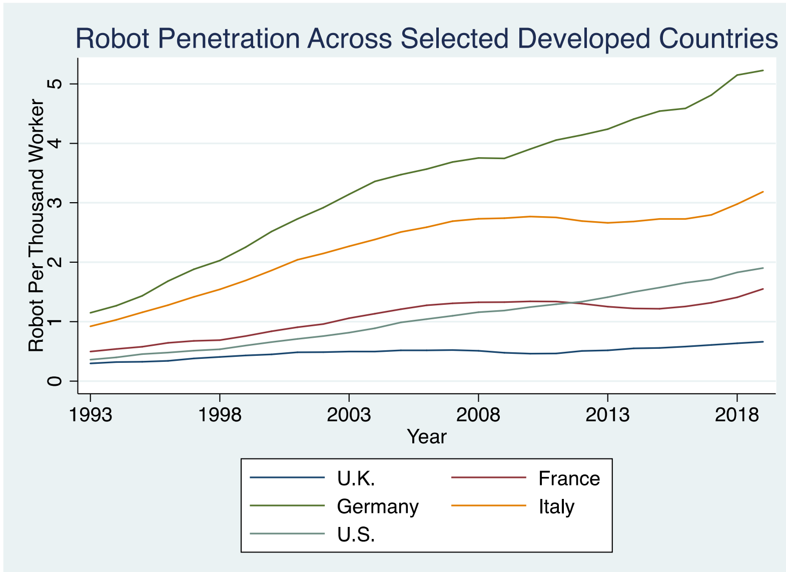
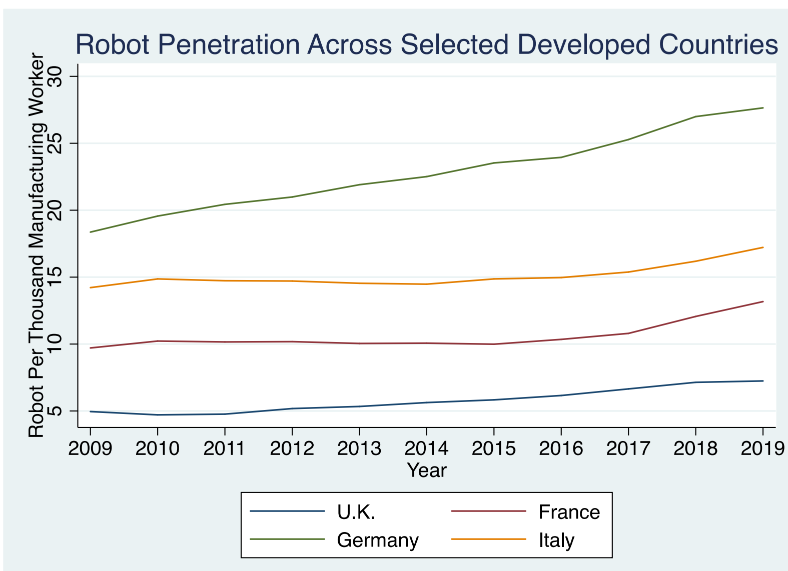
3.10 Figures and Tables

Figure 3.1: Employment-Adjusted Robot Penetration Across Major Developed Economies

Panel A: Economy-wide Robot Penetration

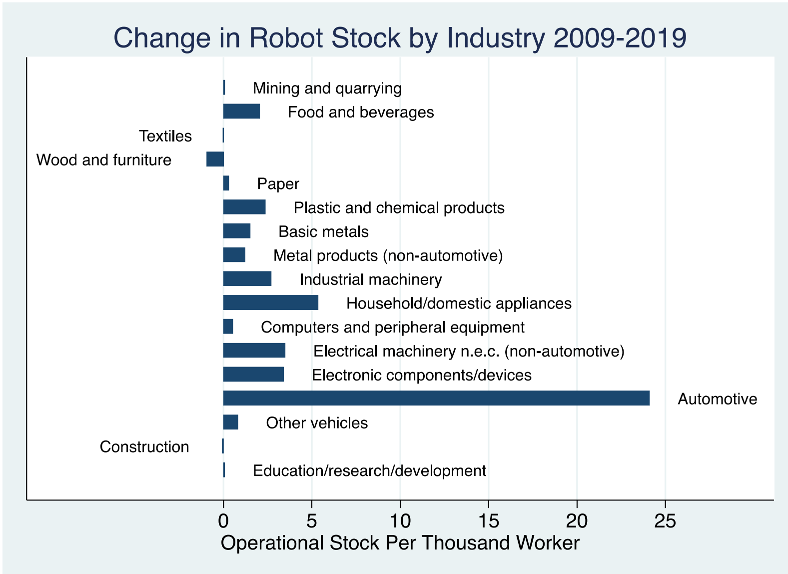


Panel B: Robot Intensity in Manufacturing Sectors



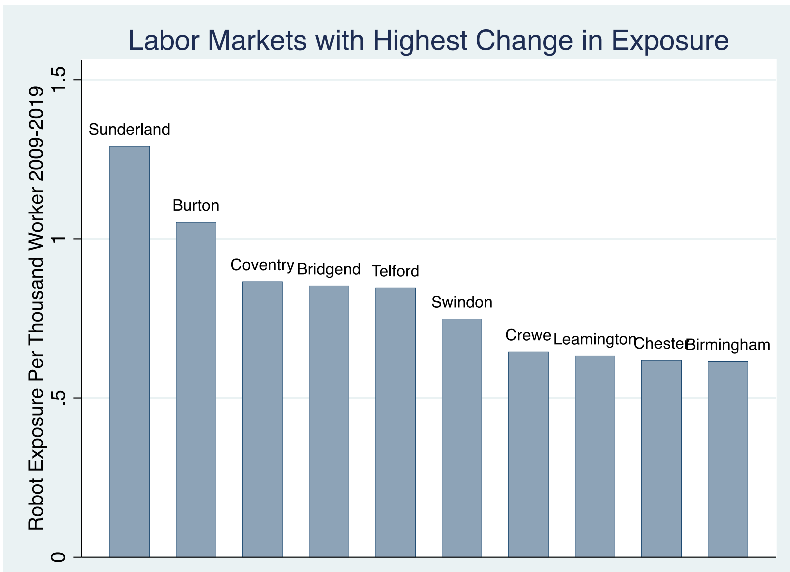
Panel A shows the trends in robot operational stock per thousand worker across selected developed countries between the years 1993 to 2019 while Panel B displays the number of robots per thousand manufacturing employment across selected developed economies between 2009 to 2019. Values for the U.S. are excluded in Panel B for data availability reasons.
Source: IFS, OECD and own calculation.

Figure 3.2: Changes in U.K. Industry-Level Robot Stock



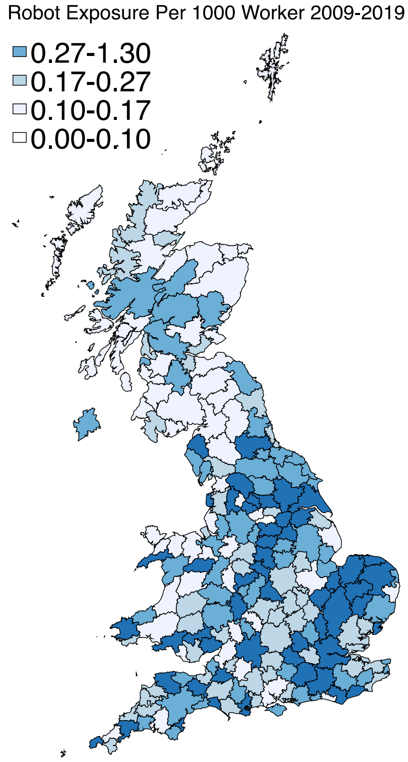
This graph shows the change in robot operational stock per thousand worker in the U.K. by industry between the years 2009 to 2019.
Source: IFR & BRES.

Figure 3.3: Local Labor Markets With the Highest Increase in Robot Penetration



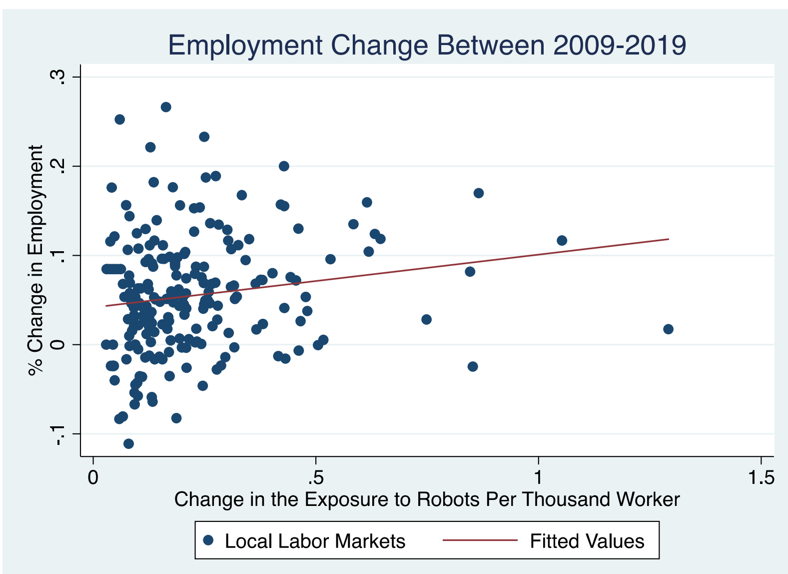
This graph shows the top ten local labor markets in Great Britain with the highest change in robot exposure between 2009 and 2019.
Source: IFR, BRES and own calculation.

Figure 3.4: Changes in Local Labor Market Exposure across Great Britain



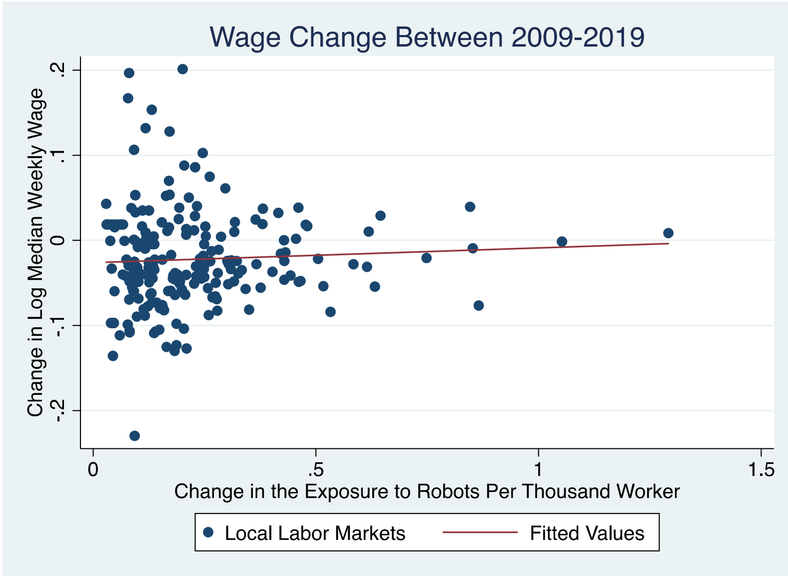
This map shows the spatial distribution of the change in robot density in Great Britain across local labor markets between the years 2009 to 2019.
Source: IFR & BRES and own calculation.

Figure 3.5: Changes in Robot Exposure and Employment



This graph plots the relationship between changes in robot exposure and the percent change in employment between the years 2009 to 2019 at the local labor market level in Great Britain.
Source: IFR, BRES and own calculation.

Figure 3.6: Changes in Robot Exposure and Median Wages



This graph plots the relationship between changes in robot exposure and the change in log median weekly wage between the years 2009 to 2019 at the local labor market level in Great Britain.
Source: IFR, ASHE, BRES and own calculation.

Table 3.1: Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Main Outcome of Interest 2009-2019					
Δ Robot Exposure (Per Thousand Worker)	212	.221	.183	.029	1.292
%Δ Total Employment	212	.056	.065	-.111	.266
%Δ Manufacturing Employment	212	.001	.152	-.407	.778
%Δ Non-Manufacturing Employment	212	.055	.073	-.146	.277
%Δ Non-Routine Employment	212	.075	.137	-.712	.422
%Δ Routine Employment	212	.023	.168	-.585	.644
Δ Weekly Wages 2009-2019 (ln)	209	-.022	.058	-.23	.201
Δ Weekly Wages [Male Full-Time] (ln)	208	-.035	.068	-.235	.172
Δ Weekly Wages [Female Full-Time] (ln)	207	.002	.069	-.233	.284
Δ Weekly Wages [Male Part-Time] (ln)	74	.04	.207	-.611	.673
Δ Weekly Wages [Female Part-Time] (ln)	197	.05	.097	-.214	.475
Industry Shares in 2009					
Agriculture & Fishing (%)	212	.053	.053	.001	.332
Manufacturing (%)	212	.106	.044	.03	.326
Mining, Energy and Utilities (%)	212	.013	.01	.003	.11
Construction Industry (%)	212	.062	.013	.024	.111
Trade & Accommodation (%)	212	.264	.034	.163	.373
Public Administration, Education and Health (%)	212	.294	.049	.157	.425
Finance, Real Estate, Professional and Administrative (%)	212	.158	.054	.057	.365
Arts, Entertainment and Other (%)	212	.049	.009	.017	.087
Education Shares in 2009					
None (%)	212	.077	.023	0	.152
NVQ1 (%)	212	.136	.033	.075	.234
NVQ2 (%)	212	.17	.026	.056	.249
NVQ3 (%)	212	.17	.022	.11	.251
NVQ4 (%)	212	.316	.06	.122	.496
Other (%)	212	.079	.017	.025	.134
Trade (%)	212	.053	.017	0	.103
Demographic Shares in 2009					
Female 2009 (%)	212	.512	.045	.264	.643
Foreign 2009 (%)	212	.038	.027	0	.198
Age 50+ 2009 (%)	212	.468	.05	.322	.629
Concurrent Trends					
Δ ICT Capital 2009-2017 (£ Pounds per worker)	212	-16.111	10.124	-52.308	12.307

This Table shows the summary statistics for all the main data and values used in the analysis. Categories expressed in brackets for wages represent the change in wages for specific demographic cells. Industries are categorized by groups of industry sections. Education categories correspond to National Vocational Qualifications (NVQ) framework. Monetary values for ICT exposure are expressed in 2010 Pounds. Wage values are expressed in 2015 Pounds.
Source: ASHE, BRES, IFR, APS, EUKLEMS and own calculation.

Table 3.2: Impact of Robot Exposure on Total Employment

VARIABLES	(1) OLS	(2) IV	(3) IV
	Δ Employment 2009-2019 (%)		
Δ Robot Exposure Per Thousand Worker	0.0180	0.0134	0.0226
	(0.0265)	(0.0252)	(0.0299)
Constant	-0.119	-0.124	-0.113
	(0.649)	(0.614)	(0.614)
Observations	212	212	212
R-squared	0.484	0.484	0.484
Cluster SE	Labor Market	Labor Market	Labor Market
Region FE	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
ICT Controls	Yes	Yes	Yes
% Education Share	Yes	Yes	Yes
% Female & % Foreign & % 50+	Yes	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	N/A	2362.92	41.24

The dependent variable is the percent change in employment at the local labor market level between the years 2009 to 2019. Robotics automation is measured by the change in the predicted local exposure to robots per thousand worker in the same period. Column 1 represents the OLS specification while Columns 2 and 3 show the IV specification where robot exposure is instrumented using changes in robot stock from 4 other developed countries. The IV specification in Column 2 is constructed treating each country as separate instruments while the IV specification in Column 3 is constructed by summing the robot installation of other nations treating it as one single country and instrument. All specifications contain a fixed effect for each nation in Great Britain. Labor markets that cross nation borders are considered one separate nation. Local industry controls include the industry shares of 9 broad industry groups. ICT exposure controls for concurrent advances in computing and communications equipment at the local level inferred using the same shift-share approach as the robot exposure measure. This is expressed using changes in the years 2009 to 2017. Education shares control for the shares of major education groups following the NVQ framework of England, Northern Ireland and Wales. Standard errors are clustered at the local labor market level. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: BRES, IFR, APS, and EUKLEMS.

Table 3.3: Impact of Robot Exposure on Median Wages

VARIABLES	(1) OLS	(2) IV	(3) IV
		Δ Median Wage 2009-2019 (ln)	
Δ Robot Exposure Per Thousand Worker	0.00788	0.0100	0.00542
	(0.0261)	(0.0263)	(0.0265)
Constant	-0.311	-0.308	-0.314
	(0.675)	(0.663)	(0.663)
Observations	686	686	686
R-squared	0.167	0.167	0.167
Cluster SE	Labor Market	Labor Market	Labor Market
Region FE	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
ICT Controls	Yes	Yes	Yes
% Education Share	Yes	Yes	Yes
% Female & % Foreign & % 50+	Yes	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	N/A	2721.59	453.65

The dependent variable is the change in log median weekly wage at the demographic-cell level between the years 2009 to 2019. Robotics automation is measured by the predicted local exposure to robots per thousand worker in the same period. Column 1 represents the OLS specification while Columns 2 and 3 show the IV specification where robot exposure is instrumented using changes in robot stock from 4 other developed countries. The IV specification in Column 2 is constructed treating each country as separate instruments while the IV specification in Column 3 is constructed by summing the robot installation of other nations treating it as one single country and instrument. All specifications contain a fixed effect for each nation in Great Britain. Labor markets that cross nation border are considered one separate nation. Local industry controls include the industry shares of 9 broad industry groups. ICT exposure controls for concurrent changes in computing and communications equipment at the local level inferred using the same shift-share approach as the robot exposure measure. This is expressed using changes in the years 2009 to 2017. Education shares control for the shares of major education groups following the NVQ framework of England, Northern Ireland and Wales. Standard errors are clustered at the local labor market level. Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05.
Source: BRES, IFR, APS, and EUKLEMS.

Table 3.4: Impact of Robot Exposure on Manufacturing & Non-Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	IV	IV	OLS	IV	IV
	Δ Manufacturing Employment 2009-2019 (%)			Δ Non-Manufacturing Employment 2009-2019 (%)		
Δ Robot Exposure Per Thousand Worker	0.181*	0.180*	0.234**	0.0219	0.0152	0.0241
	(0.0763)	(0.0714)	(0.0903)	(0.0326)	(0.0310)	(0.0368)
Constant	-1.530	-1.531	-1.465	-0.620	-0.628	-0.618
	(1.967)	(1.852)	(1.851)	(0.737)	(0.695)	(0.699)
Observations	212	212	212	212	212	212
R-squared	0.267	0.267	0.265	0.457	0.457	0.457
Cluster SE	Labor Market	Labor Market	Labor Market	Labor Market	Labor Market	Labor Market
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
ICT Controls	Yes	Yes	Yes	Yes	Yes	Yes
% Education Share	Yes	Yes	Yes	Yes	Yes	Yes
% Female & % Foreign & % 50+	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	N/A	2362.92	41.24	N/A	2362.92	41.24

The dependent variable is the percent change in employment at the local labor market level between the years 2009 to 2019. Robotics automation is measured by the predicted local exposure to robots per thousand worker in the same period. Columns 1-3 show the results for the manufacturing sector while Columns 4-6 show the results for non-manufacturing sectors. Columns 1 and 4 represent the OLS specification while Columns 2,3,5 and 6 show the IV specification where robot exposure is instrumented using changes in robot stock from 4 other developed countries. The IV specification in Columns 2 and 5 is constructed treating each country as separate instruments while the IV specification in Columns 3 and 6 is constructed by summing the robot installation of other nations treating it as one single country and instrument. All specifications contain a fixed effect for each nation in Great Britain. Labor markets that cross country borders are considered a separate country. Local industry controls include the shares of 9 broad industry groups. ICT exposure controls for concurrent advances in computing and communications equipment at the local level inferred using the same shift-share approach as the robot exposure measure. This is expressed using changes in the years 2009 to 2017. Education shares control for the shares of major education groups following the NVQ framework of England, Northern Ireland and Wales. Standard errors are clustered at the local labor market level. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: BRES, IFR, APS, and EUKLEMS.

Table 3.5: Impact of Robot Exposure on Routine & Non-Routine Employment

VARIABLES	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
	Δ Routine Employment 2009-2019 (%)			Δ Non-Routine Employment 2009-2019 (%)		
Δ Robot Exposure Per Thousand Worker	-0.101	-0.118*	-0.213*	0.121*	0.140**	0.144*
	(0.0566)	(0.0549)	(0.0889)	(0.0515)	(0.0515)	(0.0634)
Constant	-5.413**	-5.433**	-5.547**	2.182	2.204	2.210
	(1.823)	(1.721)	(1.721)	(1.686)	(1.597)	(1.598)
Observations	212	212	212	212	212	212
R-squared	0.262	0.262	0.255	0.275	0.275	0.275
Cluster SE	Labor Market	Labor Market	Labor Market	Labor Market	Labor Market	Labor Market
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
ICT Controls	Yes	Yes	Yes	Yes	Yes	Yes
% Education Share	Yes	Yes	Yes	Yes	Yes	Yes
% Female & % Foreign & % 50+	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	N/A	2362.92	41.24	N/A	2362.92	41.24

The dependent variable is the percent change in employment at the local labor market level between the years 2009 to 2019. Robotics automation is measured by the predicted local exposure to robots per thousand worker in the same period. Routine employment is defined as employment in 2-digit occupations where it is in the top tercile of routine intensity. Please refer to Appendix A-5 for the precise definitions of routine intensity. Columns 1-3 show the results for routine occupations while Columns 4-6 show the results for non-routine occupations. Columns 1 and 4 represent the OLS specification while Columns 2,3,5 and 6 show the IV specification where robot exposure is instrumented using changes in robot stock from 4 other developed countries. The IV specification in Columns 2 and 5 is constructed treating each country as separate instruments while the IV specification in Columns 3 and 6 is constructed by summing the robot values of other nations treating it as one single country and instrument. All specifications contain a fixed effect for each nation in Great Britain. Labor markets that cross nation borders are considered one separate nation. Local industry controls include the shares of 9 broad industry groups. ICT exposure controls for concurrent advances in computing and communications equipment at the local level inferred using the same shift-share approach as the robot exposure measure. This is expressed using changes in the years 2009 to 2017. Education shares control for the shares of major education groups following the NVQ framework of England, Northern Ireland and Wales. Standard errors are clustered at the local labor market level. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: BRES, IFR, APS, and EUKLEMS.

Appendix

3.10.1 Appendix A-3: Creation of Local Employment Measures and Time Series Adjustment of BRES

The Business Register and Employment Survey (BRES) is an annual government survey of firms with the aim of producing official employment statistics. Companies have a legal obligation to comply if surveyed and need to report the employment breakdown, both full time and part-time, at every operating site of the business. We recover employment data from the BRES between 2009 and 2019 at the local labor market level and at the local-industry level. The former is used as a main explanatory variable in our analysis while the latter is used to construct the robot exposure measure at the local level. We recover regional employment values at the local authority district (LAD) level. These values are then aggregated to our preferred local labor market unit at the Travel to Work Area (TTWA) level using a postcode-based crosswalk kindly provided by Max Nathan (Gutierrez-Posada et al., 2022).

There are two versions of the BRES: 1) BRES (excluding units registered for PAYE only), which is available from 2009 to 2015, and 2) BRES, which is available from 2015 to 2019. For simplicity, the first version is henceforth referred to as $BRES^{epaye}$ and the latter is referred to as $BRES^{full}$. The difference between $BRES^{epaye}$ and $BRES^{full}$ is that $BRES^{epaye}$ excludes firms registered for PAYE only. Every company in Great Britain with employees must be registered for PAYE, the U.K.'s income taxation and national insurance system, and must be registered to pay VAT above a certain turnover threshold.[47] Hence $BRES^{epaye}$ slightly undercounts total employment as it excludes employees in firms that have employees but work in firms below the thresholds for filing and paying for VAT.

As there is one year in 2015 where both versions of the BRES exist, we deploy a 'splicing' method to upwardly adjust the employment value to ensure comparability across time. We use the difference between $BRES^{full}$ and $BRES^{epaye}$ in 2015 to infer employment that is unaccounted for in $BRES^{epay}$. For the years between 2009 and 2015, we create $BRES^{adj}$ in local labor market 'l' time 't' by interacting the $BRES^{epaye}$ with 1 plus the difference between $BRES^{full}$ and

[47] The turnover threshold for VAT registration varies year to year and is between £67,000-85,000 in our sample period. Please refer to https://www.gov.uk/government/publications/vat-notice-7001-should-i-be-registered-for-vat/vat-notice-7001-supplement--2 for precise thresholds by year. Firms below this threshold can volunteer to register but must register above this threshold.

$BRES^{epaye}$ as a share of $BRES^{full}$. The equation we use is shown in Equation A-1. Hence, $BRES^{adj}$ for the years 2009 to 2015 and $BRES^{full}$ for the years 2015 to 2019 are fully comparable. The assumption that underpins the 'splicing' methodology we deploy is that the share of employment in firms not registered for VAT within each locality is constant across time.

$$BRES_{lt}^{adj} = BRES_{lt}^{epaye} * (1 + \frac{BRES_{l2015}^{full} - BRES_{l2015}^{epaye}}{BRES_{l2015}^{full}}) \quad \text{[A-1]}$$

3.10.2 Appendix A-4: Detailed List of Industries

Table A-1: Industries Covered in Analysis

Industry	Manufacturing	Granularity
Mining & quarrying	No	Sections
Food & Beverages	Yes	Groups of 2D
Textiles	Yes	Groups of 2D
Wood & Furniture	Yes	2D
Paper	Yes	Groups of 2D
Plastic & Chemical Products	Yes	Groups of 2D
Basic Metals	Yes	2D
Metal Products	Yes	2D
Industrial Machinery	Yes	2D
Domestic appliances	Yes	3D
Computers & peripheral equipment	Yes	3D
Electrical Machinery (non-Automotive)	Yes	3D
Electronic components/devices	Yes	3D
Automotive	Yes	2D
Other vehicles	Yes	2D
Construction	No	Sections
Education/R&D	No	Sections

Table A-1 in Appendix A-4 presents the list of industries covered in the analysis and their reported granularities. The industry breakdown conforms to ISIC rev 4. This includes 14 manufacturing and 3 non-manufacturing industries.

3.10.3 Appendix A-5: Routine Intensity Definition

Data on employment by occupation is obtained from the Annual Population Survey (APS) reported in 2010 SOC classifications. The most detailed occupation granularity available from the APS is at the two-digit sub-major group level with 25 distinct occupations. To determine whether an occupation is considered routine, we follow the simplified analytical classes of the National Statistic Socio-economic Classification (NS-SEC) with 7 distinct classes (ONS, 2010). An occupation is considered routine if its NS-SEC analytical class is either 'Routine' or 'Semi-Routine' defined at the four-digit occupation level. Because of the difference in the reported granularity of our data and the routine classification, we measure routine intensity by calculating the share of four-digit occupations within each two-digit occupation that are considered routine. We then define each two-digit occupation as routine if it ranks above the 66th percentile of routine intensity relative to all other sub-major occupation groups. The 66th percentile cutoff is inspired by Autor and Dorn (2013) and Dauth et al. (2021).

3.10.4 Appendix A-6: Use of Alternative Employment Measure: Employment to Population Ratio

Table A-2: Impact of Robot Exposure on Manufacturing, Non-Manufacturing, Routine, and Non-Routine Employment

VARIABLES	(1) Manufacturing	(2) Non-Manufacturing	(3) Routine	(4) Non-Routine
	Δ Employment-Population Ratio 2009-2019			
Δ Robot Exposure Per Thousand Worker	0.0158*	0.0142	-0.0413**	0.0559*
	(0.00781)	(0.0129)	(0.0156)	(0.0219)
Constant	0.00142	-0.175	-0.985**	0.972
	(0.0942)	(0.270)	(0.366)	(0.502)
Observations	212	212	212	212
R-squared	0.161	0.284	0.203	0.214
Cluster SE	Labor Market	Labor Market	Labor Market	Labor Market
Region FE	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
ICT Controls	Yes	Yes	Yes	Yes
% Education Share	Yes	Yes	Yes	Yes
% Female & % Foreign & % 50+	Yes	Yes	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	41.24	41.24	41.24	41.24

All specifications are estimated using two-stage least squares. The dependent variable is the change in employment-to-population ratio at the local labor market level between the years 2009 to 2019. Robotics automation is measured by the predicted local exposure to robots per thousand worker in the same period. Routine employment is defined as employment in 2-digit occupations where it is in the top tercile of routine intensity while non-routine employment is defined as employment in the bottom two tercile of routine intensity. Please refer to Appendix A-5 for the precise definitions of routine intensity. Columns 1-4 show the results for manufacturing, non-manufacturing, routine, non-routine occupations respectively and the specifications are analogous to Column 3 of Table 3.4, Column 6 of Table 3.4, Column 3 of Table 3.5 and Column 6 of Table 3.5 respectively. All specifications are IV specifications where robot exposure is instrumented using changes in robot stock from 4 other developed countries summing the robot values of other nations treating it as one single country and instrument. All specifications contain a fixed effect for each nation in Great Britain. Labor markets that cross nation borders are considered one separate nation. Local industry controls include the shares of 9 broad industry groups. ICT exposure controls for concurrent advances in computing and communications equipment at the local level inferred using the same shift-share approach as the robot exposure measure. This is expressed using changes in the years 2009 to 2017. Education shares control for the shares of major education groups following the NVQ framework of England, Northern Ireland and Wales. Standard errors are clustered at the local labor market level. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: BRES, IFR, APS, ONS, and EUKLEMS.

3.10.5 Appendix A-7: Use of Alternative Employment Measure: Exposure Per Thousand Manufacturing Worker

Table A-3: Impact of Robot Exposure on Manufacturing, Non-Manufacturing, Routine, and Non-Routine Employment

	(1)	(2)	(3)	(4)
VARIABLES	Manufacturing	Non-Manufacturing	Routine	Non-Routine
	Δ Employment 2009-2019 (%)			
Δ Robot Exposure Per Thousand Worker	0.0581**	0.00235	-0.0380*	0.0276*
	(0.0221)	(0.00797)	(0.0164)	(0.0136)
Constant	-1.590	-0.640	-5.394**	2.110
	(1.844)	(0.694)	(1.730)	(1.592)
Observations	212	212	212	212
R-squared	0.270	0.456	0.259	0.273
Cluster SE	Labor Market	Labor Market	Labor Market	Labor Market
Region FE	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
ICT Controls	Yes	Yes	Yes	Yes
% Education Share	Yes	Yes	Yes	Yes
% Female & % Foreign & % 50+	Yes	Yes	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	850.86	850.86	850.86	850.86

All specifications are estimated using two-stage least squares. The dependent variable is the percent change in employment at the local labor market level between the years 2009 to 2019. Robotics automation is measured by the predicted local exposure to robots per thousand manufacturing worker. Routine employment is defined as employment in 2-digit occupations where it is in the top tercile of routine intensity while non-routine employment is defined as employment in the bottom two tercile of routine intensity. Please refer to Appendix A-5 for the precise definitions of routine intensity. Columns 1 through 4 show the results for manufacturing, non-manufacturing, routine, and non-routine occupations respectively and the specifications are analogous to Column 3 of Table 3.4, Column 6 of Table 3.4, Column 3 of Table 3.5 and Column 6 of Table 3.5 respectively. All specifications are IV specifications where robot exposure is instrumented using changes in robot stock from 4 other developed countries summing the robot values of other nations treating it as one single country and instrument. All specifications contain a fixed effect for each nation in Great Britain. Labor markets that cross nation borders are considered one separate nation. Local industry controls include the shares of 9 broad industry groups. ICT exposure controls for concurrent advances in computing and communications equipment at the local level inferred using the same shift-share approach as the robot exposure measure. This is expressed using changes in the years 2009 to 2017. Education shares control for the shares of major education groups following the NVQ framework of England, Northern Ireland and Wales. Standard errors are clustered at the local labor market level. Robust standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$.
Source: BRES, IFR, APS, ONS, and EUKLEMS.

Chapter 4: Robotics Automation and Labor Market Outcomes: Evidence from Inter-Industry Linkages

4.0 Abstract

The arrival of automation technologies and how they affect employment and jobs have important socio-economic implications for individual livelihoods and the future of work with mixed evidence on its implications for workers. In this paper, we study the deployment of a specific type of automation technology, industrial robots, in the production process and how they affect labor market outcomes through inter-industry linkages, an underexplored area of analysis. Examining robotics deployment in 15 developed countries between 2005 to 2015, we find that own-industry advances in robotics automation do not cause adverse labor market outcomes. Instead, increases in robotization within industries generate significant employment effects in downstream sectors. Productivity gains originating from the arrival of robots in supplier industries raise the industry wage bill, employment, hours worked and value added of customer industries. This occurs as the gains of incorporating robotics technology are reflected in output prices, benefiting downstream industries through input price declines. Our findings highlight a channel in which the use of automation technologies such as industrial robots raises labor demand as their effects propagate across the value chain. Despite the views of those concerned of the labor consequences of an increasingly automized economy, here we provide evidence against the notion that greater rates of automation imply long run declines in labor demand as such technologies also bring about gains to labor that occur primarily outside the industries where they are introduced.

4.1 Introduction

There have been extraordinary advancements in automation technologies in recent decades with the rapid incorporation of industrial robotics and artificial intelligence technologies in the production process. Recent breakthroughs in automation and robotic capabilities have captured our imagination in the economic opportunities they bring by helping companies become leaner and more efficient (Brynjolfsson and McAfee, 2014). At the same time, the wide range of tasks that can now be performed by robots and AI technologies has created unease among workers whose jobs they may displace. More than 72% of Europeans agree with the view that robots and artificial intelligence steal peoples' jobs (European Commission, 2017). Such opinions have led to polarizing debates in the public discourse regarding the future of work in an increasingly automized economy. Will the arrival of robots and AI cause mass unemployment or will its advent be similar to any other episodes of technological change in history that the economy and workers have adapted to? On one side, some believe that recent advances in automation do not produce productivity gains that justifies its employment-displacing effects and corrective taxation ought to be used against their adoption (e.g. Acemoglu, Manera, and Restrepo, 2020). The most prominent supporter of this view is software entrepreneur and billionaire Bill Gates, who famously argued for a tax on the use of robots emphasizing that the robots that take workers' jobs do not pay income tax and hence ought be subject to additional taxation.[48] On the other hand, others argue that automation technologies do not necessarily displace employment and public policies meant to disincentivize their adoption would be counterproductive, particularly in the face of international competition (Aghion et al., 2020). Examining how the arrival of automation technologies actually affect workers across multiple dimensions could improve public discourse in understanding how best to prepare for the future of work in an increasingly automated and digitalized economy as well as help to devise appropriate policy responses if necessary.

In this paper, we study the labor market implications of a particular kind of automation, industrial robots[49], extending the analysis to incorporate cross-sector linkages and spillovers. While studies have documented the impact of industry-level robotization on economic outcomes within industries in isolation (e.g. Graetz and Michaels, 2018; Stiebale et al., 2020) as well as their dampening and reallocation effects to labor demand (e.g. Acemoglu and Restrepo, 2020; Dauth et al., 2021), little is known as to how robot adoption in one industry affects upstream and downstream sectors. The introduction of automation technologies in one sector does not just impact the sectors it is introduced in but its effects should be felt across sectors through production linkages. As a recent pertinent example, the adoption of industrial robots in the electronics and semi-conductor industry specifically has been crucial in enabling greater precision, i.e. greater efficiency, and greater speeds in the assembly process for small chips (Brumson, 2012; Smith, 2020). The embrace of automation technologies in the form of industrial robots in this particular

[48] See full story at: https://www.ft.com/content/d04a89c2-f6c8-11e6-9516-2d969e0d3b65 ; accessed on August 21st 2021.
[49] We focus on industrial robots as it is an increasingly prominent form of automation technology in recent decades both in terms of technological advancements and industry uptake. Robots are now able to perform a wide variety of tasks including welding and packaging with very little human intervention *and* world-wide robot adoption has risen by more than 150% between 1995 to 2005 (Graetz and Michaels, 2018).

industry has significant downstream consequences to any industries using semi-conductor chips as a critical input component in terms of input quantity, quality, and prices. The pandemic has also hastened trends in robotization in such industries given uncertainties in labor supply (Brown, 2020).

Robotics automation in one industry, when viewed as a technological shock, may bring out unintended but potentially positive vertical spillovers to sectors that either consume its outputs or supply its inputs through lower prices and other efficiency gains. Such mechanisms have been underexplored in the analysis of recent technological advances and studying such spillovers have the potential to unearth previously unknown economic gains from automation technologies. Using data from 15 developed countries – 12 EU countries plus U.S., U.K., and Japan – between 2005 to 2015, we study how industry robot adoption affects economic outcomes and labor markets across all industries through industry linkages. We find that robotics automation originating from supplier industries has a positive impact on own-industry economic and labor market outcomes. Robotics automation arising from input suppliers leads to higher levels of labor compensation, employment, hours worked and value added. We also provide suggestive evidence that the mechanism through which supplier efficiency gains affect customer industry labor outcomes is through input price declines; automation of supplier industries leads to productivity gains in their respective industries, resulting in cheaper inputs for customer industries and a greater own-industry consumption of those inputs. Finally, an analysis across skill groups indicates that the positive labor effects from supplier industries does not particularly bias certain skill groups, implying that the gains from productivity spillovers are likely to be broad-based.

Our analysis is among the first to examine the labor market implications of inter-industry productivity spillovers arising from a specific form of technological change: industrial robots. Accounting for input-output relationships, this study outlines a more complete picture of the overall labor market impacts arising from robotics automation technologies. Our study documents a channel in which labor demand can actually increase as a result of the introduction of automation technologies and could possibly offset the likely adverse displacement effects arising from the same technology. Our findings also point to the importance of inter-industry linkages in accounting for the gains and losses of technological change. Contrary to those who view the incorporation of new and recent automation breakthroughs in the production process as a phenomenon that may spell long run declines in labor demand, the increasing use of industrial robots and other automation technologies quite possibly creates new opportunities and raises wages but just not necessarily in the industries that have actually incorporated them.

The next section discusses some theoretical considerations of automation and summarizes related work on the topic. Section 4.3 introduces the data, methodology and the main specification used in the paper. Section 4.4 presents the main results along with accompanying findings. Finally, Section 4.5 concludes.

4.2 Literature and Discussion

There has been numerous theoretical discussions relating to automation and its labor market implications (Acemoglu and Restrepo, 2018; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). The implications of robotics automation can be viewed through the lens of the framework regarding labor-displacing technological change as described by Acemoglu and Restrepo (2018). Automation replaces a set of tasks that can be previously performed by labor, dampening labor demand, but automation also reduces the relative costs of production using labor thus discouraging future investments in automation and encourages the creation of new tasks (Ibid). Hence while the effects of automation are likely to lead to short run declines in labor demand, the long-term net effects from any form of automation technologies on labor outcomes are ambiguous and depend on the relative strength of the two competing forces. Graetz and Michaels (2018) consider the theoretical implications of advancements in robotics technology specifically at the industry level. They predict rising average wages through a productivity effect though the effects to overall labor demand is ambiguous. The net effects of robots to labor demand, they argue, depend on the firm response to robot price declines versus the consumer response to the industry output price declines caused by increased robotization.[50] Hence, these theoretical considerations lead us to hypothesize that the arrival of robotics automation technology in one industry likely has negative implications on short-run labor demand but could also lead to no net effects if other countervailing forces are also at work.

A number of empirical studies examines specifically the consequences of robotics automation. Graetz and Michaels (2018) was among the first to investigate the impacts of industrial

[50] Labor demand is expected to decline if the firm response to declines in robot prices is stronger than the consumer response to output price declines from increased automation. Conversely, changes in robot prices may increase labor demand if the consumer response to industry output price declines is large relative to the firm response to robot price declines.

robots, with data sourced from the International Federation of Robots (IFR), on productivity and labor market outcomes across country-industries. Using EU KLEMS data from 17 countries between 1993 to 2007, they find that robotization at the industry level raises labor productivity and wages. While they find modest reductions in the demand for low-skilled workers, there were no overall effects to employment and hours worked. A pair of studies (Acemoglu and Restrepo, 2020; Dauth et al., 2021) explore deeper the labor market implications of robots exploiting within-country local labor market variations in robot exposure in the U.S. and Germany respectively. Acemolgu and Restrepo (2020) finds that more than 500,000 U.S. jobs were displaced from the arrival of industrial robots while Dauth et al. (2021) finds little net employment and wage effects. Dauth et al. (2021) do show that there are heterogenous effects across industries and occupations. Jobs with task content where robots have a comparative advantage in are displaced but employment was reallocated to occupations and industries where tasks are complementary to those of robots in the production process such as managerial and technical professions. Studies have also examined the consequences from the arrival of robots at the firm level. Stiebale et al. (2020) studies the impacts of industry-level robot adoption on firm outcomes finding zero average effects but document within-industry heterogeneities. Firm sales and profits rise as a response to robotization but only for those with high initial levels of productivity and sales which, they argue, is consistent with the role of robots enhancing the 'superstar effect' or the reallocation of sales within industries towards the most productive firms (Autor et al., 2020). Acemoglu, Lelarge and Restrepo (2020) finds that individual firms that adopt robots reduce their labor share, increase their productivity *and* expand their operations and employment. This is however at the expense of non-robot adopters in the same industry, whose employment and productivity declines when their competitors adopt robots. These studies at the firm level also point to declines in labor income as well as employment at the industry level respectively (Stiebale et al., 2020; Acemoglu, Lelarge, and Restrepo, 2020). Greater rates of own-industry robotization likely has negative implications for own-industry labor market outcomes. However, past empirical studies have not explored how the introduction of robots in one industry affect other neighboring industries specifically. This is what our study intends to explore further.

Our paper is also related to past work examining the role of networks and how shocks propagate across the economy through production and value-chain linkages (Javorcik, 2004; Antras et al., 2012; Carvalho, 2014; Acemoglu et al., 2015; Acemoglu et al., 2016). Acemoglu et al. (2015) proposes a framework to assess how economic shocks transmit across sectors through industry linkages. They predict that supply-side shocks in one industry create powerful downstream propagation but has minimal impacts to upstream sectors. Positive (negative) productivity shocks transmit downstream because of its impacts on own-industry output prices – leading to lower (higher) input prices paid by consumer industries with corresponding changes to their production. Such shocks also correspondingly lead to downstream effects to labor market outcomes as positive shocks cause consumer industries to raise (lower) labor demand so their production levels calibrate accordingly. Supply shocks, though, do not transmit upstream because the price and quantity effects to upstream industries exactly offset each other.[51] Conversely, demand shocks disseminate upstream through commensurate changes in input demand leading to zero downstream effects. When experiencing positive (negative) demand shocks, affected industries raise (lower) their output accordingly with proportional changes to their input demand, affecting their suppliers. Downstream effects from demand shocks are absent given constant returns to scale with demand shocks resulting in only quantity responses and not prices. Motivated by their theoretical predictions, they empirically test four distinct economic shocks[52], two demand and two supply, on the U.S. economy and find the consequences of these shocks to be consistent with their framework. Autor and Salomons (2018) examine how automation, inferred using changes in productivity growth, relates to patterns of labor demand after accounting for production linkages using Acemoglu et al. (2015)'s framework. While industry productivity growth lower own-industry labor outcomes, productivity growth from supplier industries raises own-industry employment and hours worked, with the own-industry effects from automation almost entirely offset by the positive spillovers from upstream sectors. Technological change in the form of robotics technology, when viewed through the lens of Acemoglu et al. (2015)'s framework, would be considered a supply shock to the sector. Higher robotics adoption ought to generate positive downstream spillovers to customer sectors through price mechanisms. Consistent with this framework, Graetz and Michaels (2018) show empirically the possibility of this spillover mechanism at work documenting lower output prices from increased robot adoption, implying that robotization upstream could benefit downstream sectors and final consumers. Autor and Salomons

[51] Acemoglu et al. (2015) argues that consistent Cobb-Douglas production technologies and household preferences cancels out the price and quantity effects.
[52] The two demand shocks they examined were import competition and government spending while the supply shocks they tested were changes in TFP and foreign patenting.

(2018) demonstrate that productivity growth dampens own-industry labor demand but its effects spill over positively to customer industry labor demand. Their findings lend support to the notion that there could be positive labor market effects across industries from the arrival of robots. The discussions up to this point naturally lead us to conjecture a potential positive effect to downstream labor market outcomes in a given industry from the arrival of a specific technology that raises productivity such as robotics automation in upstream industries and that such spillovers likely operate through price channels. We thus build on past work by Autor and Salomons (2018) and Graetz and Michaels (2018) and extend the input-output framework to explore the labor market consequences of robotics automation *specifically* across industries.

Finally, our paper relates to a number of studies on the impacts of automation and technological change on labor market consequences across the skill distribution (Autor and Dorn, 2013). The falling cost of automation, particularly of routine tasks through advances in ICT technology, has led to significant shifts in labor demand across skill types with a decline in demand for those with intermediate skills and a corresponding rise at either end of the skills distribution commonly referred to as labor market polarization (Goos et al., 2014; Michaels et al., 2014). Motivated by the labor market adjustments brought upon by past waves of technological change, Graetz and Michaels (2018) studies specifically the influence of robotics automation on the relative changes in labor demand across the skill distribution, finding instead that it is those at the lowest end of the skill spectrum who lose out the most. We will build on their work and examine how supply shocks generated by robotics automation affect the relative economic position of workers in downstream sectors across the same skill orientations.

4.3 Data and Methodology

4.3.1 Data

Data on industrial robots is sourced from the International Federation of Robots (IFR), a professional non-profit organization whose mission is to strengthen and promote the robotics industry worldwide (IFR, 2020). A robot, as defined by the IFR, is an ‘automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes.’ (Ibid). The IFR collects annual data on the number of robot installations and operational stock through a survey of major robot suppliers covering more than 90% of all world-wide robot installations. Data is available at the country-industry level with varying industry granularities. Industry economic data are obtained from EU KLEMS including value added, employment, hours worked, and technological assets, among others (Stehrer et al., 2019). To account for industry linkages, we use input-output tables at the country level from the OECD (2018) with data on input and output consumption and their associated weights across industries. Input-Output Tables are a common tool to assess input-output relationships across sectors for the purposes of analyzing trade and value added flows across industries. For the sake of simplicity, we ignore sectoral trade across countries and focus only on input-output linkages for domestic industries within a country deploying input consumption weights recorded in the year 2005[53] in our analysis. All data sources report industries using ISIC Rev. 4 classifications. Industry granularity is reported either at the two-digit level or in groups of two-digit industries with the detailed breakdown of each industry reported in Table 4.1. We focus our attention on 15 countries[54] and 28 industries across the years 2005 to 2015[55] where comprehensive data is available.[56] This set of countries comprises of more than 50% of world GDP across our sample period. All monetary values are reported in and converted to 2010 U.S. Dollars.

One complication is that the IFR only report robot installation and stock breakdown for a select group of mostly manufacturing industries. The lack of data in some industries poses a problem for our purposes of analyzing spillovers across industries, which requires information on robotics exposure in all industries. The IFR data does contain information on all industries but a complete industry breakdown across some industries would not be meaningful because of the low rates of robot adoption in many industries outside of manufacturing and robot installation information in such industries are instead placed in the industry category of 'all other non-manufacturing'[57] according to IFR representatives.

[53] As we are examining changes between the years 2005 to 2015, the input weights during this period could be endogenous to the industry-specific robot adoption patterns we are examining. For instance, industries could be altering their input consumption patterns precisely towards sectors that have experienced productivity gains through robotization during this period. This motivates our choice of using the weights in the beginning period only.

[54] The countries we examine are Austria, Belgium, The Czech Republic, Germany, Denmark, Spain, Finland, France, Italy, Japan, Netherlands, Sweden, Slovakia, U.K. and the U.S.

[55] We focus on our attention on this period primarily due to data constraints. Comprehensive coverage for EU KLEMS for most countries terminate in 2015 while input-output tables for the most recent industry classification – ISIC Rev. 4 – only began in 2005. Analyzing robotics technology earlier than this period would be less meaningful given the low rates of robot adoption before the 2000s (e.g. Graetz and Michaels, 2018).

[56] In a later part of the analysis examining the distributional consequences by skill type, the data granularity and coverage is reduced. The analysis in this particular section will utilize data from 14 countries, 16 industry sections, covering the years 2008 to 2015 instead.

[57] This category represents no more than 1% of the number of robots installed in any given year between 2005 to 2015.

To overcome this issue of non-reporting in some industries, we infer data on robot stock by using the robot information in the 'all other non-manufacturing' category. First, we assume that the number of robots in use in all non-reported industries are uniform relative to their share of gross value added. We then take the value of robot stock for each country-year for the industry category of 'all other non-manufacturing' and interact it with each non-reported industries' share of value added as a total of all remaining value added.[58] This approach allows us to recover an imputed value of robot adoption for industries that were not separately reported. Table 4.1 reports the full list of industries used in the analysis and whether the robot penetration measure was separately reported or imputed.

4.3.2 Specification

We deploy a five-year differences specification with two non-overlapping periods between 2005 & 2010 and 2010 & 2015[59] denoted in Equation 1

$$\Delta lnY_{i,c,t} = \Delta lnR_{i,c,t} + \Delta\tilde{R}_{i,c,t}^{SUPP} + \Delta\tilde{R}_{i,c,t}^{CUST} + \Delta\emptyset_{i,c,t} + C_c + IP_{it} + \varepsilon_{i,c,t} \quad [1]$$

The change in the log of outcome variable 'Y' in industry 'i' country 'c' time 't' is regressed against the log change of robots in operational stock of industry 'i' country 'c' time 't' itself and also the change in robot adoption of industry 'i''s suppliers (upstream) as well as its customers (downstream). The outcome variable 'Y' would be an array of industry-level labor and economic outcome available from EU KLEMS including employment, hours worked, wage bill, and value added. The terms '$\Delta\tilde{R}_{i,c,t}^{SUPP}$' and '$\Delta\tilde{R}_{i,c,t}^{CUST}$' capture the weighted sum of the change in robot adoption in the suppliers and customers of industry 'i' respectively and their calculations are expressed in Equations 2 and 3 respectively. Inspired by Graetz and Michaels (2018), the vector term '$\emptyset_{i,c,t}$' denotes controls including changes in capital intensity[60] as well as concurrent changes in ICT[61] technologies. As robot purchases are both a form of capital investment and technological

[58] The value added of the industries which do report installation data is stripped out for the calculation.
[59] While our time period partially overlaps with the financial crisis, we believe the fixed effects we've incorporated in the specification along with the suite of controls we've deployed is sufficient to absorb such concerns specific to the time period.
[60] This is expressed as the change in the ratio of the log share of capital compensation to the log share of labor compensation.
[61] This is measured by the log change in the gross fixed capital formation of computing, communications and software technologies as a share of total gross fixed capital formation.

change, the inclusion of these controls is meant to ensure that robotization patterns during our period of analysis are not just capturing trends in capital deepening and other kinds of concurrent but distinct forms of automation technology. Country and industry-period fixed effects, represented as 'C_c' and 'IP_{it}' respectively, are deployed to eliminate the unobserved heterogeneity of country-specific shocks and industry trends in robot adoption.[62] The use of industry-period fixed effects is especially warranted as the robot adoption trends in certain industries are inferred as described in the previous section.[63] As industries are reported in different granularities, we weigh our specification by the within-country share of industry value added interacted with the country's share of total value added in our sample. Standard errors are clustered at the country-industry level.

$$\Delta\tilde{R}_{i,c,t}^{SUPP} = \sum_{j=1}^{J} Leontief_{j,c,t}^{SUPP}\, x\, \Delta \ln R_{j,c,t}^{SUPP} \quad [2]$$

$$\Delta\tilde{R}_{i,c,t}^{CUST} = \sum_{j=1}^{J} Leontief_{j,c,t}^{CUST}\, x\, \Delta \ln R_{j,c,t}^{CUST} \quad [3]$$

We follow Autor and Salomons (2018) and express supplier and customer linkages in Equations 2 and 3 respectively. The estimated robot exposure from all supplier (customer) industries is calculated as the change in log robot operational stock in supplier (customer) industry 'j' interacted with the domestic Leontief inverse weights of supplier (customer) industry 'j' where 'j' does not equal industry 'i'.[64] These values are then summed across all industry 'j's that comprise of all the suppliers (customers) of industry 'i'. The Leontief supplier (customer) weights assigned to industry 'j' capture the importance of suppliers (customers) industry 'j' in the production (as end consumers) of industry 'i'. These weights capture the full set of input-output relationships among all domestic industries.[65]

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[62] We deploy country and industry-period fixed effects given that rates of robot adoption rates have gone through dramatic changes during this period and are highly heterogenous across industries.

[63] As we do not directly observe the robot adoption patterns for some **industries** across our sample period, eliminating unobserved heterogeneity across along industry-specific trends is crucial to the robustness of the specification.

[64] As the reported industries in the OECD is slightly different from those that can be matched to EU KLEMS and the IFR robot data, we recalculate the Leontief Weights using raw domestic consumption relationships across sectors using the equation: $(\mathbf{I} - \mathbf{A})^{-1}$ where I is the identity matrix and A represents the matrix where each scalar is domestic industry 'i''s consumption of domestic industry 'j''s goods as a share of the total output of domestic industry 'i'.

[65] The Input-Output relationships of domestic industry 'i' with the rest of the world are ignored for the sake of simplicity. While some domestic industries may source inputs or sell goods and services abroad, the shares each industry 'i' consume or sell to each supplier or customer industry 'j', irrespective of their domestic or foreign status, should remain largely be the same. Even in the case of industries with substantial cross-country linkages such as the automotive industry, input consumption shares with or without incorporating such linkages would not be meaningfully different as the production process of making cars is still the same i.e.

4.3.3 Descriptive Evidence

We begin with an overview summarizing the evolution of robot adoption trends and labor market dynamics with an emphasis on the distinction between industries with actual robots data and industries with imputed values using our approach. Table 4.2 presents the summary statistics of the changes of our labor market outcomes of interest along with the patterns of robot adoption between 2005 to 2015. Panel A presents figures for the sample of industries with which robot data are available while Panel B displays values for the set of industries where robot adoption developments are inferred. Meanwhile, Panel C shows the full sample. To reiterate, industries with actual reported robot data available, shown in Table 4.1, are predominantly manufacturing industries where industrial robots are widely used. Such industries represent approximately half of the total count number of industries. For industries whose robot values are inferred in Panel B, the estimated values of robot penetration in the starting year of our analysis and its subsequent changes compared to industries in Panel A are much lower. This is a result of the reported values for robot penetration in the industry category of 'all other non-manufacturing' being not very high to begin with. While such values seem low, we argue that such imputed values do capture actual adoption rates of these industries as they do not adopt many robots if at all. As mentioned earlier, we will eventually deploy the use of industry-period fixed effects to eliminate unobserved heterogeneity to alleviate concerns of the unevenness of robot adoption across industries. Examining specifically the domestic Leontief weights, we see that covered industries have a slight lean to be supplier or upstream sectors as indicated by its higher supplier weights while non-covered industries have a tendency to be customers given its higher reported customer or downstream weights. When looking at the full sample across all industries in Panel C, we observe that the average of the downstream and upstream Leontief weights is exactly the same reflecting the identity properties of the weights as every industry is equally both a customer and a supplier to other industries.

automotive manufacturing requires the same amount of inputs at aggregated industry levels including steel, plastics, and electronic components, among other materials regardless of where such inputs are sourced.

4.4 Results

4.4.1 Main Results

Table 4.3 presents the five-year differences specification showing the estimated impacts of own-industry robot adoption on an array of economic and labor market outcomes for all industries. Across the specifications, an increase in industry-level robot adoption is associated with broadly positive labor market outcomes leading to higher total wages paid, employment and hours worked though the effects of the latter two are not significant. Though industrial robot use is often seen as task-displacing in production, these empirical findings are largely consistent with Graetz and Michaels (2018), showing that robot adoption has minimal effects on industry-level labor market outcomes. Column 4 in Table 4.3 shows that increases in robots are strongly associated with gains to value added, which is not surprising given its demonstrated productivity-enhancing effects. To check the consistency of the results of the inference method we adopted for non-reported industries as described in the data section, Table A-1 in the Appendix A-8 presents the same specifications as Table 4.3 with only industries with actual reported robot adoption data. The comparison in the estimates across the two samples lend support to our approach of using imputed values in non-reported industries as the results are largely the same. Finally, Table 4.4 presents the empirical results incorporating both the robot adoption of customer and supplier industries in addition to the own-industry exposure for all industries. Across all columns, we observe that increases in the robot adoption of supplier industries have a positive influence on all the economic outcomes of interest, as a 10% increase in the automation of suppliers is associated with an approximately 0.3% increase in industry employment and total hours worked and a 1.4-1.7% increase in industry total labor compensation and value added. Robotics automation arising from customer industries, by contrast, exhibits little to no impact on own-industry outcomes, with the exception of a slight positive influence on value added. However, such an effect is minimal compared to those arising from upstream sectors with supplier influences inducing more than ten times the magnitude to industry value added. The addition of industry linkages in the specification does alter the own-industry effects as own-industry robot adoption is no longer meaningfully associated with own-industry gains to labor compensation and value added.[66]

[66] The disappearance of the own-industry effects after incorporating inter-industry linkages can be explained by the correlation of robot adoption across industries along the value chain and the presence of downstream propagation of automation shocks as shown in Table 4.4. As robotization of production has been a global phenomenon, adoption of robots across industries is likely correlated

The comparatively strong influence arising from supplier industry automation patterns and the lack of own-industry influences in explaining own-industry outcomes after incorporating industry linkages demonstrates that the productivity dividends in upstream sectors is markedly higher than those of own-industry effects, highlighting the importance of incorporating sector spillover effects. The decoupling of own-industry automation patterns from gains in industry value added after taking into account industry linkages in the specification do suggest that robot adoption trends are likely to be correlated across industries along the supply chain and that the observed spillover effects from robot adoption in one specific industry to all other industries are not uniform, highlighting possible heterogeneities in automation externalities. This will be explored further in subsequent sections. Our general finding that the inter-industry productivity spillovers from automation advances in one industry mostly flow to their customer industries is consistent with the framework outlined by Acemoglu et al. (2015), which documents strong downstream propagation of productivity shocks but limited upstream effects.

4.4.2 Endogeneity

Robot adoption at the industry level, of course, is not random. Industries that have the most potential to gain from incorporating robotics technology in their production process would likely purchase more robots resulting in a selection bias between own-industry robot adoption and industry economic outcomes. Past studies have overcome this issue by instrumenting robot adoption with variations in industry-level exposure to robotics automation based on task content and with the robot adoption trends of other countries, constructing plausibly exogenous causal estimates of their impacts within industries (e.g. Graetz and Michaels, 2018; Stiebale et al., 2020). Our study, focusing on the effects of robot adoption in one industry on the labor market outcomes of other industries i.e. interaction between upstream and downstream sectors, is much less susceptible to the endogeneity issues from selection bias as identified by past work that focuses solely on economic relationships within industries. Stakeholders that determine the robot adoption in one industry are unlikely to take into account the labor market consequences in other sectors when devising its automation plans. Conversely, it is also difficult to imagine industries base labor

in practice. Hence the own-industry effects and estimates in Table 4.3 (without incorporating industry linkages) may be upwardly biased because own-industry robotics automation is collinear with the automation of its suppliers, thereby capturing the effects from robotization upstream.

demand decisions predominantly on the automation capabilities of their customer or supplier industries alone, an equally improbable reverse causality scenario. Furthermore, there are considerable practical difficulties at implementing and imbedding a suitable identification strategy within the input-output framework with multiple countries, industries and time periods in the analysis. Hence, with respect to our main analysis investigating spillover effects *across* industries, we do not envision major concerns of endogeneity and conclude that our current specifications are sufficient to establish a well-identified empirical relationship.

4.4.3 Mechanism

Economic shocks that transmit across supplier and customer linkages are captured both through quantity and price effects. In this section, we focus on the possible mechanisms of how robot adoption affect industry supply chains vertically by testing its relationship with inputs and outputs as well as prices directly.[67] Our outcome variable of interest is the log change in input (output) values in Column 1 (Column 2) of Table 4.5 as well as the log change in the producer price index of inputs (outputs) in Column 3 (Column 4). In Columns 1 and 2 of Table 4.5, we uncover evidence to suggest that supplier robotics automation increases both own-industry consumption of inputs *and* production of outputs. In Columns 3 and 4 of Table 4.5 where we examine the price indices directly, we show that supplier robot adoption lowers both own-industry input and output prices and that own-industry advances in robots lead to a decline in output prices, albeit insignificantly. These findings, automation arising from suppliers lowering input prices and own-industry automation lowering output prices, show the same downstream forces at work and appear to aptly chronicle the mechanism in which the positive labor market spillovers, as documented earlier, operate through industry linkages. The insignificance of the positive effects found for own-industry automation on own-industry output prices as shown in Column 4 of Table 4.5 is somewhat concerning as there is potentially insufficient evidence to establish the industry-to-industry link via prices. To investigate further, we, in Table A-2 in Appendix A-9, replicate the empirical set up in Table 4.5 but remove the measures on sectoral linkages from the specification and solely examine own-industry influences. In this specification, we show, in Column 4 of Table A-2, that own-industry robot adoption do in fact lower own-industry output prices in isolation. The

[67] Our analysis on inputs, outputs and their prices excludes the U.K. and Spain because of lack of data.

results from both Table 4.5 and Table A-2 of Appendix A-9 do in fact corroborate price channels as the main mechanism in which such spillovers operate. We conclude that the absorption of the own-industry effects after incorporating sector linkages is suggestive of confounding influences and the presence of possible non-linearities in the spillover effects arising from upstream industries.[68]

Such findings on inputs, outputs, and their prices, taken together, are consistent with the inter-industry network framework outlined by Acemoglu et al. (2015) that the effects of supply shocks accruing to downstream sectors are operating through price channels. Robotics automation in one industry leads to a decline in the prices paid by industries that consume its outputs. When experiencing such price declines, consumer industries then in turn purchase more inputs and hire greater quantities of labor to produce higher levels of output at a lower price, leading to further downstream effects. This price effect plausibly accounts for the role of how greater advances in automation technologies in one industry are felt and disseminated across the rest of the economy. By zooming in on the price and quantity movements across industries as a response to automation, we show that the mechanism in which productivity shocks such as robotics automation benefits neighboring industries operates through price responses.

4.4.4 Skill Distribution

The adoption of automation technologies has implications for overall labor demand across industries but they can also have important distributional consequences. Automation can create winners and losers across the labor market within occupations and sectors in addition to their economy-wide effects. Past work has demonstrated meaningful differential impacts from automation along skill divides (Autor and Dorn, 2013; Michaels et al., 2014). In this section, we attempt to determine whether the positive spillover effects of robotics adoption arising from

[68] We argue that the insignificance of own-industry automation patterns to own-industry outcomes after incorporating linkages can be explained by the fact that industry robot adoption is correlated across the supply chain within countries and the addition of such linkages in the specification captures this collinearity between Table 4.5 and Table A-2. After accounting for industry linkages, the fact that supplier robot adoption still remain influential and more so than own-industry robot adoption in determining own-industry output prices is suggestive of unevenness in the observed downstream propagation across supplier-to-customer links. The downstream propagation of supply shocks is more powerful in some supplier-customer links than others but is still nonetheless carried forward continuously throughout across the value chain affecting all industries. While own-industry robot adoption still do meaningfully affect own-industry output prices as shown in Table A-2 of Appendix A-9, its effects are more muted considering the collinear patterns and simultaneous input price shocks. While our analysis ignores final demand consumption, the fact the automation to output price link is more pronounced in particular strands of the supply linkage could be indicative of stronger spillover effects in industries traditionally further away from final goods consumption such as mining or utilities.

supplier industries we've documented vary across the skill distribution. Graetz and Michaels (2018) assess whether own-industry automation in the form of robotics specifically lead to relative changes in labor demand across workers of different skill groups within the same industry. They document that increases in robot penetration lead to declines in the relative share of hours worked for the lowest skilled group. Building on their work, we set out to explore whether increases in robot penetration from upstream and downstream sectors translate to relative gains or losses for workers of varying skill. We focus our attention on the relative share of total employment and compensation by three different skill groups.[69] Our outcome variable of interest is the change in the log share of employment and the total wage bill share by each skill group times 100. The time, country, and industry coverage are reduced because of data availability for this particular outcome of interest. Hence, in this section, we utilize the same estimating specification using Equation 1 but instead restrict our attention to outcomes between the years 2008 to 2015 in 16 industries and 14 countries analyzing changes in two three-year periods: 2008 to 2011 and 2012 to 2015. Columns 1&2, 3&4, and 5&6 of Table 4.6 report the results for low, medium and high skill groups respectively. Columns 1,3 and 5 in Table 4.6 report the results for the change in the relative share of total employment by skill groups while Columns 2, 4 and 6 display the results for the change in the total wage bill share. Consistent with the results from Graetz and Michaels (2018), we find that own-industry robot deployment leads to a modest, though unsignificant, decline in the relative labor market position of the lowest skill group. As our analysis up to this point demonstrates the importance of downstream spillovers, we find higher robot adoption of suppliers to be associated with positive, albeit insignificant, relative gains for low-skill groups while we observe ambiguous, and also insignificant, effects for high-skill groups. Conversely, we document a general decline of the relative labor market position of medium-skill groups from automation in upstream sectors as shown in Columns 3 and 4 with a modest but statistically meaningful contraction of their relative employment share. While such results may be an indication that the spillover effects we documented earlier could bias certain skill groups – in particular those at either end of the skill distribution at the expense of those in the middle – consistent with labor market polarization trends, the results are not statistically influential across most of the specifications. We instead interpret the largely ambiguous results we've documented and their weak magnitudes across skill groups to

[69] The three categories of skill type are low, medium, and high. Low refers to workers without formal qualifications. High refers to university graduates. The medium skill group refers to workers with skill levels in between the two groups. These categories capture all workers as the combined shares sum to one for each country-industry.

suggest that the observed gains to labor at the industry level from supplier automation advances documented earlier are not biased towards any particular skill group.

4.5 Conclusion

The increasing use of automation technologies in the economy has many fearing that one day their jobs might be replaced with robots or other machines. We thus attempt to contribute to the understanding of the labor and economic implications of recent automation advancements by examining the case of industrial robot adoption and its productivity externalities across industries. We build on past work and incorporate vertical spillovers in examining the consequences of robotics automation on upstream and downstream sectors. By using an imputed approach to infer robot adoption in missing industries and the use of Input-Output tables, we are able to recover an industry-level automation exposure in all industries, including spillover effects, within an economy and fully account for sectoral linkages. Analyzing rates of robot adoption in 15 countries between 2005 and 2015, we find that the arrival of robot technologies mostly generates downstream pressures as consistent with theory. Higher robotization arising from supplier industries raises industry value added and output and its effects outweigh those arising from own-industry automation advancements. Increases in the robotization of suppliers also raise industry-level total labor compensation, employment and hours worked. We also find that the mechanism of how the effects of robot technologies diffuse across sectors work through price movements. Industries experiencing rising levels of automation through the increased use of robots lower their output prices, leading to downstream consequences. Industries that are their consumers, when experiencing such price declines, procure more inputs and raise labor demand as a response to produce more output. We also do not find significant distributional consequences from downstream spillovers when zooming in on the effects across the skill distribution. Our results demonstrate that automation, particularly in the realm of industrial robot use, do not have significant adverse labor market impacts to the economy and sectors downstream to industries where robotics automation originates from may actually benefit from higher levels of compensation and greater rates of employment. Our results also document the importance of accounting for vertical spillovers when examining the impacts of the arrival of new technologies as a failure to account for industry linkages would provide an incomplete picture of the net impacts of automation as much of the economic gains may accrue to other industries.

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4.7 Tables

Table 4.1: List of Industries

Industry Code	Industry	Granularity	Data Status
A	Agriculture; forestry and fishing	Sections	Imputed
B	Mining and quarrying	Sections	Actual
10-12	Manufacture of food products beverages, tobacco products	Divisions	Actual
13-15	Manufacture of textiles, wearing apparel, leather and related products	Divisions	Actual
16-18	Manufacture of wood products, paper products, printing of media	Divisions	Actual
19	Manufacture of coke and refined petroleum products	Divisions	Imputed
20-21	Manufacture of chemicals and chemical products	Divisions	Actual
22-23	Manufacture of rubber, plastics and other non-metallic mineral products	Divisions	Actual
24-25	Manufacture of basic & fabricated metal products, except machinery	Divisions	Actual
26-27	Manufacture of computer, electronic, optical and electrical equipment	Divisions	Actual
28	Manufacture of machinery and equipment	Divisions	Actual
29-30	Manufacture of motor vehicles, trailers, and other transport equipment	Divisions	Actual
31-33	Furniture and other manufacturing; Machinery repair & installation	Divisions	Actual
D-E	Utilities	Sections	Actual
F	Construction	Sections	Actual
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	Sections	Imputed
H	Transportation and storage	Sections	Imputed
I	Accommodation and food service activities	Sections	Imputed
58-60	Publishing, video, song programming and broadcasting activities	Divisions	Imputed
61	Telecommunications	Divisions	Imputed
62-63	Information service activities & Information service activities	Divisions	Imputed
K	Financial and insurance activities	Sections	Imputed
L	Real estate activities	Sections	Imputed
M-N	Professional, scientific, technical, administrative and support service activities	Sections	Imputed
O	Public administration and defense; compulsory social security	Sections	Imputed
P	Education	Sections	Actual
Q	Human health and social work activities	Sections	Imputed
R-S	Arts, entertainment and recreation & Other service activities	Sections	Imputed

Table 4.1 presents the list of industries used in the analysis, their granularity and their data status. The list of industries correspond to ISIC Rev 4. classifications. The data status ‘Actual’ refers to the case when there is existing industry data on robot installations. The data status ‘Imputed’ refers to the case when there is no industry data on robot installations from the data source. The robot installations in imputed industries are inferred using the robot installation for the industry category ‘all other non-manufacturing’ in that country-period interacted with the ratio of the within-country value added of that industry as a share of the total value added of all industries where robot installations were not available. Robot values for Industry 19 are imputed as they are not available as a result of slight discrepancies in reporting granularity across data sources.

Table 4.2: Descriptive Statistics of Industries by Data Type

Variable	Obs	Mean	Std.Dev.	Min	Max
Actual			Panel A		
Robots-2005 (ln)	204	4.335462	3.147816	0	11.72655
Robots-Own (Δ ln)	204	.190926	1.46859	-4.29046	5.811141
Robots-Customer (Δ ln)	204	.615577	1.03578	-1.18749	7.252161
Robots-Supplier (Δ ln)	204	.664637	.517863	.042334	2.526247
Leontief Customer Weights	204	.393149	.333768	.007945	1.910822
Leontief Supplier Weights	204	.617274	.193369	.113503	1.121452
Wage Bill (Δ ln)	204	.156218	.184543	-.460835	.874406
Employment (Δ ln)	204	-.110814	.2152	-.849575	.527995
Hours (Δ ln)	204	-.124749	.215769	-.852568	.536124
Labor Share (Δ ln)	204	.008879	.176923	-.47776	1.45017
Value Added (Δ ln)	204	-.084103	.342312	-1.13652	2.188096
Imputed			Panel B		
Robots-2005 (ln)	208	.006886	.018858	0	.109064
Robots-Own (Δ ln)	208	.109634	.658796	-2.682028	1.728418
Robots-Customer (Δ ln)	208	.543602	1.337239	-.000042	11.17347
Robots-Supplier (Δ ln)	208	.489477	.394174	-.701716	1.799446
Leontief Customer Weights	208	.726008	.773947	.005437	3.826622
Leontief Supplier Weights	208	.504309	.150839	.161701	.952711
Wage Bill (Δ ln)	208	.12052	.173544	-.472662	.84342
Employment (Δ ln)	208	.049557	.188935	-.663131	.675119
Hours (Δ ln)	208	.026073	.189151	-.715843	.611479
Labor Share (Δ ln)	208	.009032	.197903	-1.510431	.600273
Value Added (Δ ln)	207	.041211	.467281	-4.635999	1.716931
Full Sample			Panel C		
Robots-2005 (ln)	412	2.150162	3.096672	0	11.72655
Robots-Own (Δ ln)	412	.149886	1.133801	-4.29046	5.811141
Robots-Customer (Δ ln)	412	.57924	1.196588	-1.18749	11.17347
Robots-Supplier (Δ ln)	412	.576207	.467334	-.701716	2.526247
Leontief Customer Weights	412	.561194	.620056	.005437	3.826622
Leontief Supplier Weights	412	.560243	.182004	.113503	1.121452
Wage Bill (Δ ln)	412	.138196	.179747	-.472662	.874406
Employment (Δ ln)	412	-.02985	.217479	-.849575	.675119
Hours (Δ ln)	412	-.048606	.216136	-.852568	.611479
Labor Share (Δ ln)	412	.008956	.18758	-1.510431	1.45017
Value Added (Δ ln)	411	-.020989	.41432	-4.635999	2.188096

Table 4.2 presents the summary statistics of our main economic outcomes of interest along with robot adoption. The values are reported in log changes between the years 2005 to 2015. The sample of industries labeled ‘Actual’ refers to the sample of industries where industry breakdowns of robot installations are available. The data status ‘Imputed’ refers to the case when there is no industry data on robot installations from the data source. The robot installations for imputed industries are inferred using the robot installation for the industry category ‘all other non-manufacturing’ in that country-period interacted with the ratio of the within-country value added of that industry as a share of the total value added in industries where robot installations were not available.

Source: EU KLEMS, IFR, and OECD.

Table 4.3: Impacts of Own-Industry Robot Adoption on Labor Outcomes

	(1)	(2)	(3)	(4)
VARIABLES	Wage Bill	Employment	Hours Worked	Real Value Added
Δ Log (Robots)	0.0593***	0.00706	0.00780	0.0389*
	(0.0131)	(0.00629)	(0.00746)	(0.0158)
Constant	0.162	-0.00550	-0.0250	0.0217
	(0.0924)	(0.0174)	(0.0229)	(0.0573)
Observations	821	821	821	821
R-squared	0.608	0.568	0.542	0.469
Trend Controls	Yes	Yes	Yes	Yes
Industry-Period FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
SE Cluster	Country-Industry	Country-Industry	Country-Industry	Country-Industry
Model Weight	Value Added	Value Added	Value Added	Value Added

Table 4.3 uses a differences specification based on five-year changes between 2005-2010 and 2010-2015. The outcome variable of interest is highlighted underneath the column number. They are expressed as the difference in log values. The independent variable of interest represents the change in the log number of robots in operational stock. For industries without robot coverage, robot stock is inferred by taking the number of robot in operational stock in all other non-manufacturing industries and interacting the value with the industry's within-country share of value added in all unreported industries. Trend controls include the log change in the ratio of capital to labor services as well as the log change in the share of ICT capital. All specifications incorporate country and industry-period fixed effects. Standard errors are clustered at the country-industry level. Each specification is weighted by the within-country share of value added interacted with the country share of the total value added of all countries in the sample. Robust standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$.
Source: EU KLEMS, IFR, and OECD.

Table 4.4: Impacts of Robot Adoption on Labor Outcomes

VARIABLES	(1) Wage Bill	(2) Employment	(3) Hours Worked	(4) Real Value Added
Δ Log (Robots)	0.0334	0.00332	0.00551	0.000668
	(0.0195)	(0.0106)	(0.0127)	(0.0160)
Δ Log (Robots) —Customers	0.00381	-0.00109	-0.00223	0.0121*
	(0.00645)	(0.00368)	(0.00431)	(0.00615)
Δ Log (Robots) —Suppliers	0.155***	0.0358*	0.0348*	0.174***
	(0.0278)	(0.0163)	(0.0174)	(0.0262)
Constant	0.0727	-0.0281	-0.0481	-0.0713
	(0.0621)	(0.0231)	(0.0290)	(0.0384)
Observations	821	821	821	821
R-squared	0.676	0.577	0.550	0.550
Trend Controls	Yes	Yes	Yes	Yes
Industry-Period FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
SE Cluster	Country-Industry	Country-Industry	Country-Industry	Country-Industry
Model Weight	Value Added	Value Added	Value Added	Value Added

Table 4.4 uses a differences specification based on five-year changes between 2005-2010 and 2010-2015. The outcome variable of interest is highlighted underneath the column number. They are expressed as the difference in log values. The independent variable of interest represents the change in the log number of robots in operational stock. For industries without robot coverage, robot stock is inferred by taking the number of robots in operational stock in all other non-manufacturing industries and interacting the value with the industry's within-country share of value added in all unreported industries. Trend controls include the log change in the ratio of capital to labor services as well as the log change in the share of ICT capital. All specifications incorporate country and industry-period fixed effects. Standard errors are clustered at the country-industry level. Each specification is weighted by the within-country share of value added interacted with the country share of the total value added of all countries in the sample. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: EU KLEMS, IFR, and OECD.

Table 4.5: Impacts of Robot Adoption on Inputs, Outputs and Prices

VARIABLES	(1) Input	(2) Output	(3) Input Prices	(4) Output Prices
Δ Log (Robot)	0.00950	-0.00134	-0.00997	-0.00453
	(0.0326)	(0.0205)	(0.00573)	(0.00323)
Δ Log (Robot) —Customers	0.0131	0.0142	-0.000113	-0.000777
	(0.0122)	(0.00826)	(0.00208)	(0.00118)
Δ Log (Robot) —Suppliers	0.213***	0.192***	-0.0303***	-0.0276***
	(0.0334)	(0.0282)	(0.00690)	(0.00547)
Constant	-0.0349	-0.0382	0.171***	0.163***
	(0.0628)	(0.0537)	(0.0186)	(0.0161)
Observations	710	710	710	710
R-squared	0.497	0.578	0.649	0.746
Trend Controls	Yes	Yes	Yes	Yes
Industry-Period FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
SE Cluster	Country-Industry	Country-Industry	Country-Industry	Country-Industry
Model Weight	Value Added	Value Added	Value Added	Value Added

Table 4.5 uses a differences specification based on five-year changes between 2005-2010 and 2010-2015. The outcome variable of interest is highlighted underneath the column number. They are expressed as the difference in log values. The independent variable of interest represents the change in the log number of robots in operational stock. For industries without robot coverage, robot stock is inferred by taking the number of robots in operational stock in all other non-manufacturing industries and interacting the value with the industry's within-country share of value added in all unreported industries. Trend controls include the log change in the ratio of capital to labor services as well as the log change in the share of ICT capital. All specifications incorporate country and industry-period fixed effects. Standard errors are clustered at the country-industry level. Each specification is weighted by the within-country share of value added interacted with the country share of the total value added of all countries in the sample. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: EU KLEMS, IFR, and OECD.

Table 4.6: Impacts of Robot Adoption on Labor Outcomes Across the Skill Distribution

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Employment %	Wage Bill %	Employment %	Wage Bill %	Employment %	Wage Bill %
	Low-Skill Groups		Medium-Skill Groups		High-Skill Groups	
Δ Log (Robot)	-0.0395	-0.0121	0.00325	0.00361	0.0198*	0.0174
	(0.0230)	(0.0290)	(0.00688)	(0.00947)	(0.00999)	(0.0131)
Δ Log (Robot) —Customers	0.0124	0.00719	-0.000546	0.000166	-0.00366	-0.00127
	(0.00656)	(0.00775)	(0.00190)	(0.00252)	(0.00430)	(0.00465)
Δ Log (Robot) —Suppliers	0.0570	0.0292	-0.0285**	-0.0241	0.00763	-0.00604
	(0.0305)	(0.0358)	(0.0101)	(0.0145)	(0.0209)	(0.0207)
Constant	-0.0482	-0.110**	-0.0326	0.0223	0.321***	0.164***
	(0.0584)	(0.0376)	(0.0270)	(0.0330)	(0.0621)	(0.0371)
Observations	446	446	446	446	446	446
R-squared	0.361	0.297	0.272	0.417	0.319	0.383
Trend Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Cluster	Country-Industry	Country-Industry	Country-Industry	Country-Industry	Country-Industry	Country-Industry
Model Weight	Value Added	Value Added	Value Added	Value Added	Value Added	Value Added

Table 4.6 uses a differences specification based on three-year changes between 2008-2011 and 2012-2015. The outcome variable of interest in Columns 1, 3 and 5 is the log change in the employment share of each respective skill group while the outcome variable in Columns 2, 4 and 6 is the log change in the total wage bill share of each respective skill group. Columns 1-2, 3-4, and 5-6 show the results for low, medium, and high skill groups respectively. The outcome variable in all specification is the log change in the share of the outcome variable times 100. The independent variable of interest represents the change in the log number of robots in operational stock. For industries without robot coverage, robot stock is inferred by taking the number of robots in operational stock in all other non-manufacturing industries and interacting the value with the industry's within-country share of value added in all unreported industries. Trend controls include the log change in the ratio of capital to labor services as well as the log change in the share of ICT capital. All specifications incorporate country and industry-period fixed effects. Standard errors are clustered at the country-industry level. Each specification is weighted by the within-country share of value added interacted with the country share of the total value added of all countries in the sample. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: EU KLEMS, IFR, and OECD.

4.8 Appendix

4.8.1 Appendix A-8

Table A-1: Impacts of Own-Industry Robot Adoption on Labor Outcomes-Partial Sample

	(1)	(2)	(3)	(4)
VARIABLES	Wage Bill	Employment	Hours Worked	Real Value Added
Δ Log (Robot)	-0.00297	-0.00526	-0.00607	-0.0117
	(0.0113)	(0.0120)	(0.0127)	(0.0194)
Constant	0.202*	0.0215	0.00619	0.0520
	(0.0873)	(0.0258)	(0.0313)	(0.0639)
Observations	408	408	408	408
R-squared	0.653	0.596	0.597	0.447
Trend Controls	Yes	Yes	Yes	Yes
Industry-Period FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
SE Cluster	Country-Industry	Country-Industry	Country-Industry	Country-Industry
Model Weight	Value Added	Value Added	Value Added	Value Added

Table A-1 uses a differences specification based on five-year changes between 2005-2010 and 2010-2015. This specification only includes industries with reported robot installation data from the IFR. The outcome variable of interest is highlighted underneath the column number. They are expressed as the difference in log values. The independent variable of interest represents the change in the log number of robots in operational stock. Trend controls include the log change in the ratio of capital to labor services as well as the log change in the share of ICT capital. All specifications incorporate country and industry-period fixed effects. Standard errors are clustered at the country-industry level. Each specification is weighted by the within-country share of value added interacted with the country share of the total value added of all countries in the sample. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.
Source: EU KLEMS, IFR, and OECD.

4.8.2 Appendix A-9

Table A-2: Impacts of Own-Industry Robot Adoption on Inputs, Outputs and Prices

	(1)	(2)	(3)	(4)
VARIABLES	Input	Output	Input Prices	Output Prices
Δ Log (Robot)	0.0547*	0.0423*	-0.0143***	-0.00931**
	(0.0220)	(0.0175)	(0.00364)	(0.00300)
Constant	0.0859	0.0684	0.152***	0.146***
	(0.101)	(0.0859)	(0.0222)	(0.0182)
Observations	710	710	710	710
R-squared	0.402	0.467	0.631	0.733
Trend Controls	Yes	Yes	Yes	Yes
Industry-Period FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
SE Cluster	Country-Industry	Country-Industry	Country-Industry	Country-Industry
Model Weight	Value Added	Value Added	Value Added	Value Added

Table A-2 uses a differences specification based on five-year changes between 2005-2010 and 2010-2015. The outcome variable of interest is highlighted underneath the column number. They are expressed as the difference in log values. The independent variable of interest represents the change in the log number of robots in operational stock. For industries without robot coverage, robot stock is inferred by taking the number of robots in operational stock in all other non-manufacturing industries and interacting the value with the industry's within-country share of value added in all unreported industries. Trend controls include the log change in the ratio of capital to labor services as well as the log change in the share of ICT capital. All specifications incorporate country and industry-period fixed effects. Standard errors are clustered at the country-industry level. Each specification is weighted by the within-country share of value added interacted with the country share of the total value added of all countries in the sample. Robust standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$.
Source: EU KLEMS, IFR, and OECD.

Chapter 5: Residential Land-use Regulation and Local Growth: Evidence from U.S. Metropolitan Areas.

5.0 Abstract

There is an increasing awareness of the affordability problems caused by building restrictions in U.S. cities. Despite effectively working to limit the expansion of localities, local restrictions on land use are often instinctively associated with above average economic performance. In this paper, we examine the local growth consequences of restrictions on land use across U.S. metropolitan areas. Greater land-use restrictions do not lead to differential growth outcomes on net though we document substantial differences after local house price variation is taken into account. In fact, we show that total output growth and the output growth of the construction sector are differentially affected in the face of demand pressures but only when house price movements are netted out. This, we contend, can be explained by land-use regulation's second order effect to local growth through consumption channels via house prices in addition to its binding constraints to employment and construction in the presence of demand pressures. We conclude that relaxations in the local land-use planning regime are unlikely to alter local growth rates on its own but can shift the underlying sources of growth.

5.1 Introduction

Local regulatory restrictions on land use have been blamed for much of the rise in house prices across U.S. cities in recent decades by restricting new residential developments, contributing to an ever-growing affordability crisis. Consequently, many localities, recognizing the housing supply and price problems associated with such restrictions, have made attempts to liberalize zoning laws. Recently, California has approved a slew of amendments to state law overriding many of the most restrictive sets of regulations by localities, which is estimated to lead to the development of up to 700,000 new homes (Metcalf et al., 2021). Other notable deregulatory initiatives have also occurred in regions such as Oregon, Minneapolis, among others.

Despite the role land-use restrictions play in constraining the use of an important input of production – land – and in impeding new units of housing to come online supported with theoretical and empirical evidence, it is often correlated with high economic activity. Superstar cities such as New York, San Jose, among others have managed to achieve high levels of both output and output growth while maintaining the most restrictive land-use practices in the nation (Gyourko et al., 2013; Hsieh and Moretti, 2019; Kemeny and Storper, 2020). It is evident that the relationship between land-use practices and growth outcomes is likely to be a complicated one.

While the impacts of local land-use regulation on housing supply and prices have been well established and extensively reviewed[70], comparatively less is known about the local economic consequences of restrictive land-use policies. The empirics of the economic impacts of land-use regulation and the potential gains from deregulation or 'up-zoning' have been widely debated in recent years (Glaeser and Gyourko, 2018; Rodriguez-Pose and Storper, 2020). High degrees of land-use regulation have been shown to depress the economic activity of various sectors *and* decrease the responsiveness of construction and employment activity to local demand fundamentals. On the other hand, land-use regulation, when pair with an outward shift in demand, ought to lead to higher expected levels of house price growth, which could possibly fuel greater rates of economic expansion through consumption channels. No study, to the best of our knowledge, has attempted to directly examine the link between supply constraints on housing and city level output growth. Given recent interests and gaps in the literature, we study this issue in depth. Assessing the relationship between local land-use regulation and economic performance would serve to clarify the somewhat puzzling observational correlation between the two metrics as well as to provide some guidance on the likely economic impacts from recent deregulatory efforts.

We examine the relationship between regulations on housing and local growth in 229 Metropolitan Statistical Areas (MSAs) in the United States using the Wharton Residential Land Use Regulatory Index (WRI) between the years 2006 to 2011. Deploying the use of a panel interaction specification and complementing the analysis with instrumental variables, we show that increases in regulatory constraints, when viewed in relation to local demand, do not cause any differential effects to the local growth of total output or output per person during the period. However when local house price dynamics are accounted for, we find that land-use regulation depresses the transmission of local demand to total output growth *but* not for output growth per capita. Similarly, we find that the output growth of the construction industry is also affected from

[70] For instance, see Gyourko and Molloy (2015).

greater rates of restrictiveness, again only when house price effects are netted out. The results *after* netting out house price effects are consistent with the notion that land-use regulation acts to reduce the responsiveness of *both* employment and construction activity to local demand shocks in accordance with past work. The discrepancies we've identified from the effects of land-use regulation can be explained by the presence of two distinct and simultaneous channels at work in which land-use regulations affect growth. Tight restrictions to land use do indeed cause cities to experience slower growth than what would be the case based on their demand fundamentals in high demand localities. Concurrently, the interaction of high demand and tight supply influences also generates house price responses that causes upward pressure to local growth through consumption channels via increases in the housing net worth and relaxations in the borrowing constraints of local households. The net of the two forces leads regulation to exhibit no overall effects to local growth outcomes.

Restrictive land-use policies do not itself affect growth outcomes per say. Rather, we infer that land-use regulation likely alters the composition of growth when localities experience the same demand pressures. In high-regulation areas, such forces are reflected in growth in the form of increases in local consumption and non-tradeable sector employment through gains in housing net worth. In low-regulation areas, by contrast, the same demand fundamentals are manifested locally through increases in construction activity and in-migration. Our results highlight an additional influence regulatory restrictions could have on local economic outcomes not by influencing overall levels of growth but by reshaping the structures of economic change in cities.

The next section presents the related literature and discussion on the topic. Section 5.3 presents the data and methodology while Sections 5.4 and 5.5 present and discuss the main results respectively. Finally, Section 5.6 concludes.

5.2 Land-use Regulation and Economic Performance

Regulatory constraints on housing are laws, ordinances and policies that govern the nature of housing developments within localities. As housing regulations often entail the regulation of land, it is synonymous with the term land-use regulation though land-use regulation encompasses land use of all types. The welfare economics view of land-use regulation suggests that in an urban environment rife with externalities, land-use regulation could correct the market failures associated with proximity by governing the use of land within cities (Hilber and Robert-Nicoud, 2013).

Welfare gains, for instance, could be achieved by separating land for residential and industrial use so the negative externalities associated with industrial production do not spillover to residential neighborhoods or by protecting views and open spaces valued by the public that may not necessarily exist as private agents do not take into account the social surpluses from their existence (Cheshire and Sheppard, 2002; Turner et al., 2014). Evidence suggest that residents do value the gains from limits on land use including open spaces and protected views (Cheshire and Sheppard, 2002; Glaeser et al., 2005).

While land-use regulation could in principle lead to welfare gains, there is a consensus in the literature that regulatory constraints raise house prices by limiting housing supply, particularly in the U.S. (Katz and Rosen, 1987; Quigley and Raphael, 2005; Ihlanfeldt, 2007; Glaeser and Ward, 2009; Saiz, 2010). The United Kingdom faces a similar problem with regulatory constraints accounting for a substantial portion of the house price gains since 1974 (Hilber and Vermeulen, 2016). Tighter regulation's direct role in raising house prices is also omnipresent in other countries including South Korea (Green et al., 1994), Thailand (Mayo and Shepard, 1996) and Malaysia (Bertaud and Malpezzi, 2001). While it is intuitive and empirically well-founded that regulations on housing impact house prices, the impacts of regulation on local economic performance have been less extensively studied.

Regulations on housing could depress local growth by decreasing the responsiveness of population/employment and construction growth from demand shocks. More workers and individuals would have moved to certain localities for greater employment prospects in the face of rising local demand pressures but are deterred from doing so from a combination of low quantities of new housing and rising house prices in restrictive areas in response to the same demand pressures. Instead of a response in employment and new housing construction activity from such shocks, they raise house prices and wages instead in constrained locations (Hilber and Vermeulen, 2016; Ganong and Shoag, 2017; Hsieh and Moretti, 2019). There is ample evidence to suggest this is the case. Glaeser et al. (2006) documents that a demand shifter is expected to have more than triple the effect on population growth in unconstrained U.S. metropolitan areas relative to those with very restrictive regulatory regimes on housing development. Saks (2008) also finds that demand shocks to localities can differ significantly according to their levels of regulation showing that employment growth is more than 20% higher in U.S. localities with less legal constraints on house building. Hsieh and Moretti (2019) demonstrate, in a counterfactual reallocation exercise, that lowering housing regulation in the three most productive U.S. cities to that of the median city could triple their employment totals. Construction activity, particularly in housing, is affected through the same mechanism as physical and regulatory limitations on housing lead to fewer investments in the housing sector and reduce the responsiveness of construction investments from local demand (Mayer and Somerville, 2000; Paciorek, 2013; Ganong and Shoag, 2017; Albouy and Ehlrich, 2018). The above discussion suggests that local GDP growth could be lowered in the presence of limiting constraints on housing development through lowered employment and construction activity in response to the same demand factors.

Land-use regulations have also been shown to distort productivity growth, particularly in the housing sector. Albouy and Ehrlich (2018) estimate the production function for housing in U.S. cities, showing that land-use regulation reduces housing construction productivity. Regulation raises house prices more so than predicted changes in land and construction costs thus driving a wedge between prices and inputs. Waights (2019), using the same framework, examines the distortions brought upon by Conservation Area designations in the U.K., a form of heritage conservation policy which restricts housing and land-use changes in targeted neighborhoods. A one standard deviation increase in local Conservation Area designation is shown to decrease housing construction productivity by up to 5%. Finally, land-use regulations on housing may impact local productivity indirectly through agglomeration mechanisms by placing constraints on population and employment. The productivity advantages of larger and denser cities are well known (Duranton and Puga, 2004) and past studies have estimated the wage-productivity elasticities with respect to city size and density to be between 0.02 and 0.05. i.e. a doubling of scale leads to a 3-6% increase in wages and productivity (Ciccone and Hall, 1996; Combes and Gobillon, 2015; De la Roca and Puga, 2017). By inadvertently capping urban growth, regulations on housing could lead to lower local productivity growth in the long run by forgoing the productivity benefits from enhanced agglomeration forces.

Elsewhere, land-use regulation in domains outside of residential land has been shown to also dampen growth in specific sectors of the economy, particularly in space-intensive industries. Cheshire and Hilber (2008) examine the commercial property market in the U.K. and Europe, suggesting that regulations raise the cost of commercial floor space relative to its marginal cost of construction. Their results show that regulation raises the price of floor space by more than 80 to 800% in European and U.K. cities, raising the cost for all firms that require office space. Cheshire et al. (2015) examines the adoption of restrictive land use measures in the U.K. on local retailers, which inhibited their location choice and capacities. They find a nearly 30% reduction in retail productivity of a specific U.K. grocer following the full implementation of such policies. Suzuki (2013) studies the effects of land-use regulation on the hospitality sector in Texas. Greater land-use regulation, in this instance, was found to have reduced hotel offerings, increased prices, operational costs and raised barriers to entry in the industry. The above discussion points to land-use regulation being detrimental to industry-specific productivity, independent of the effects of housing specific land-use regulation. As land, irrespective of their specified use, are close substitutes on the margins, restrictions on non-residential land use do still have important implications for the economic impacts of residential supply constraints given potential spillover effects.

While much of the discussion on the economic consequences of land-use regulation considers their adverse and distortionary implications, regulations on residential land use, especially when paired with simultaneous demand forces, could nevertheless exert a second order effect to economic performance through their influence to house prices. As discussed previously, there is an established consensus on the tight link between regulatory constraints on housing and house prices (Gyourko and Molloy, 2015). Meanwhile, house price movements, though, have also been shown to significantly determine local consumption patterns through changes in household wealth and collateral constraints (Girouard and Blöndal, 2001; Campbell and Cocco, 2007; Mian et al., 2013; Mian and Sufi, 2014; Aladangady, 2017). Exploiting the timing of the financial crisis and the geographic variation of housing net worth across U.S. housing markets, Mian et al. (2013) demonstrates the importance of local housing net worth fluctuations to consumption as they estimate a large elasticity of consumption with respect to housing net worth at up to 0.8. Follow-up work by Mian and Sufi (2014), examining the same housing net worth shock to local employment and distinguishing between tradeable and non-tradeable sector employment, confirms that the flows from changes in housing wealth to consumption is highly localized in nature.[71] Hence, the mechanisms outlined suggest that the house price response from restrictions on land use interacted with demand forces may lead to a similar consumption reaction from households,

[71] Mian and Sufi (2014) show changes in housing net worth only affect local non-tradable sector employment and have no impact to local tradable sector employment. As the local non-tradable sector depends primarily on demand originating locally while the local tradable sector is more diversified in its geographic origins of demand, Mian and Sufi's results affirm the local economic effects originating from fluctuations in local housing net worth shocks.

affecting local economic performance. This is a channel which, under certain conditions, could see land-use regulation indirectly leading to positive influences to growth outcomes. Such a mechanism can possibly counteract the discussed detrimental economic impacts of land-use regulation.

Finally, this paper also relates to a growing literature on the macroeconomic effects of aggregate spatial misallocation from local land-use regulation (Herkenhoff et al., 2019; Hsieh and Moretti, 2019; Parkhomenko, 2020). High house prices in prosperous parts of the country as a result of tight regulation measures prevent additional workers from moving in to take advantage of the productivity benefits of high-wage cities, resulting in an inefficient allocation of labor nationwide. Hsieh and Moretti (2019) show U.S. aggregate output could be up to 9% higher from deregulation in only the cities of San Jose, San Francisco and New York City. Herkenhoff et al. (2019) finds rolling back regulation to 1980 levels in California and New York could boost total productivity by up to 7%. The above discussion shows two possible opposing forces at work in how land use regulation may affect local growth. In the presence of demand forces, land use regulation can dampen local growth by deterring population and construction growth but could possibly serve to amplify growth through consumption channels via house price mechanisms. Hence, the economic effects of land use regulation is ultimately an empirical question and further analysis is warranted to assess how land use regulation actually affect local economic performance.

5.3 Data and Methodology

5.3.1 Empirical Specification

We start by specifying the main panel empirical specification used in the analysis as shown in Equation 1. Our main outcome of interest is the difference in the log of output ‘Y’ in metropolitan area ‘m’ between time ‘t’ and ‘t-1’, which effectively captures the yearly growth rate of each metropolitan area. This is regressed against a measure of local demand, denoted as ‘D_{mt}’ and our main measure of land-use regulation is denoted as ‘Reg_m’.[72] In order to control for supply restriction(s) to local housing unrelated to regulations, we additionally introduce a vector term ‘Osc_m’, also interacted with local demand, covering other related constraints restricting residential

[72] Our specification explicitly focuses on the joint impacts or interaction effects of regulation and demand on local growth. The independent or direct effects of regulation is not assessed as our measure of regulation, which is time-invariant, is netted out in the fixed effects specification.

growth; the details of which will be outlined in the next section. As regulations, a supply-side phenomenon, should not affect local growth independently of demand, land-use regulations and other possible supply-side constraints are interacted with measures of local demand denoted as 'D_{mt}' in the specification. To control for convergence effects and the sensitivity of growth to past output values, we deploy the log output of each metropolitan area in the previous year '$Ln(Y)_{mt-1}$' in the specification. Metropolitan area and year fixed effects, denoted as 'Mfe_m' and 'Tfe_t' respectively, are also deployed to control for time-invariant local features as well as time-specific shocks that affect growth respectively. As metropolitan areas represent functional economic boundaries, we assume little spillover effects across local units.[73] All values in the interaction specification are demeaned for an easier interpretation of the coefficients. Finally, standard errors are clustered at the metropolitan area level.

$$Ln\,(Y)_{mt} - Ln(Y)_{mt-1} = D_{mt} + Reg_m\, x\, D_{mt} + Osc_m x\, D_{mt} + Ln(Y)_{mt-1} + Mfe_m + Tfe_t + \varepsilon \qquad [1]$$

5.3.2 Data

The most common approach to measure the stringency of local planning constraints is to survey communities on their practices of land-use planning (Katz and Rosen, 1987; Linneman et al., 1990; Gyourko et al., 2008, Glaeser and Ward, 2009). For our analysis, we use the Wharton Residential Land Use Regulatory Index (WRI) as the measure of regulatory constraints (Gyourko et al., 2008). The WRI is an aggregate index that measures the level of regulatory constraints on housing developments in U.S. municipalities and was created from a mass survey conducted in 2005 with more than 2,600 municipality responses.[74] The index covers an exhaustive list of formal barriers to residential development, including local political pressure, state involvement, zoning approval, supply, density, open space restrictions and approval delays, among others. The index is standardized with a mean and standard deviation of zero and one respectively. High values indicate a more stringent regulatory regime while low values reflect a more relaxed approach towards housing development. Figure A in Appendix A-10 provides a list of example questions in the

[73] We assume little spatial spillovers across metropolitan areas as MSAs have self-containment rates (the share of residents who work within the metropolitan area they reside in) of over 90%.
Source: ACS.

[74] The survey was sent to the Planning Director of the municipality, if the office existed. Otherwise, it was sent to the Chief Administrative Officer (Gyourko et al., 2008). The response rate was approximately 38%, representing over 60% of the U.S. population.

survey sent out to each municipality. We utilize estimates of the WRI at the metropolitan level obtained from aggregating the municipal level index using sample weights available from Saiz (2010).[75]

Physical barriers to local residential development unrelated to regulatory barriers could also influence growth outcomes. They include both topographical features that restrict the amount of land suitable for development as well as existing settlement patterns that limit the remaining amount of developable land. Such constraints may exert similar effects to growth compared to that of land-use regulation, when paired with the same shocks to local demand, and these features should be accounted for in the specification. We introduce local features, denoted as 'Osc_m', that measure physical constraints to residential growth and separately interact them with demand forces. To capture geographical constraints, we utilize the share of undevelopable land in a metropolitan area within a 50 km radius of the central city as measured by Saiz (2010). Land is considered undevelopable if it sits on bodies of water or on an incline of more than 15 degrees. Building on land with slopes above 15 degrees, according to Saiz (2010), makes development very costly from a construction and engineering standpoint, rendering such land essentially 'undevelopable'. Next, we proxy for the degree of existing development using the sprawl index developed by Burchfield et al. (2005) for the year 1992. This index captures the percentage of undeveloped land in the square kilometer surrounding an average residential development. Higher values indicate that local residential housing is more spread out and implies fewer available land for new developments.

For local growth measures, we obtain output data at the county level from the Bureau of Economic Analysis (BEA). Metropolitan areas are largely a county-based measure of urban boundaries and output at the metropolitan area can be directly recovered through upward aggregation. The BEA reports breakdowns of local GDP along with the local output values of all component industries. Finally, as the specification relies on a measure of demand, we proxy local demand with local employment levels. Employment data is recovered by interacting population values and employment rates available from the American Community Survey (ACS), both of which are sourced from the Census Bureau (CB). Metropolitan area values from both the Census and the ACS are extracted via the IPUMS portal (Ruggles et al., 2021).

[75] As the WRI index at the metropolitan level is aggregated from municipal level values, its values could be sensitive to the aggregation weights used. Saiz (2010, p. 1261) points out that the variation of WRI values across metropolitan areas is robust to a variety of alternative weighing schemes.

5.3.3 Instruments

Measured regulatory constraints on housing are likely to encounter issues of endogeneity in its relation to local growth. Economic growth may systemically influence the incentive to enact greater restrictions on new housing development hence local regulations could reflect past growth. Local residents may prefer to enact stricter regulations on development as a response to the negative congestion externalities associated with greater rates of in-migration that growth may imply. If so, the regulatory measure would also be capturing local demand in addition to supply conditions, leading to biased results. As land-use regulation is locally determined, contemporaneous measures of housing regulation could also be correlated with unobservable local characteristics that affect economic outcomes. To account for such endogeneity issues, we instrument land-use regulation, the WRI index, with a measure of static time-invariant urban amenities. Hilber and Robert-Nicoud (2013) proposes that local characteristics that affect the value of land will change the incentives to regulate land. As jurisdictions exhibit innate differences in amenities across locations and households prefer amenity-rich areas, there would be more demand for high amenity locations. To prevent a rise in negative congestion externalities from in-migration, households and landowners, either to preserve their amenity levels or land values, have an incentive to raise local development restrictions, which would be reflected through local land-use regulation (Gyourko and Molloy, 2015). Hence, high levels of amenities in a locality are expected to be positively related to constraints on development. We deploy Albouy's Quality of Life index (2008) of U.S. metropolitan areas measured in 2000 as a proxy for urban amenities. The index captures all forms of amenities including crime, culture and dining options as well as physical measures of temperature and coastal proximity. Physical amenities such as topographical and weather-related measures, which do not change over time, are exogenous to problems of reverse causality and ought not to be correlated with unobservable characteristics that relate to contemporaneous rates of growth. We recover Albouy's index stripped of time-varying amenity features, which includes only variations from coastal proximity, sunshine, warm winters and mild summers, as an instrument. It is reassuring to note that after removing the time-varying features from the index, variations in weather and geography still account for over 70% of the difference in amenities across U.S. cities ensuring that the index remain relevant while exogenous as an instrument.

Relevantly, demand, as captured by local employment, is also subject to endogeneity concerns in its relations with supply-side constraints as changes in local demand may also influence local incentives to regulate residential land-use. Rising local employment levels could spark concerns of overcrowding and congestion from the local populace, which when reflected in zoning laws, could lead to greater restrictions on local residential land use as a remedy to constrain urban growth. Hence, local demand could simultaneously lead to a supply-side response as well, ruling out a causal interpretation in a naïve OLS setting. Furthermore, given that demand shifts in regulated localities are known to exert a strong local price response through housing, the composition of local employment shifts could very well be different in such localities as productive economic activity sort to more expensive locations, resulting in a selection bias. To account for such concerns, we deploy a Bartik-style instrument as a local shifter for demand. Our Bartik instrument utilizes industry composition shares from the year 1980 interacted with national level changes in industry employment. The construction of our demand shifter 'D_{mt}^{iv}' follows Equation 2 where the employment of industry 'j' metropolitan area 'm' in the year 1980 is interacted with the national growth rate of industry 'j' between time 't' and 1980. These values are then summed across all 'j's with 13 unique industries.[76] All values are incorporated in the specification as logged values.

$$D_{mt}^{iv} = \sum_{j=1}^{J} emp_{jm1980} \ x \ 1 + \frac{emp_{jt} - emp_{j1980}}{emp_{j1980}} \qquad [2]$$

5.3.4 Summary Statistics

Table 5.1 displays the data used in the analysis for the year 2006 only. We utilize 1999 definitions of Metropolitan Statistical Areas.[77] The WRI along with the unavailable land share, sprawl and amenities measures are time invariant across the sample period and their reference years are 2006, 1992 and 2000 respectively. Output data is measured in thousands of chain 2012 dollars and growth data are reported in log differences. For example, the growth data for the year 2006 is the difference in the log outputs of the years 2006 and 2005. As the WRI was constructed

[76] The 13 industries include agriculture, mining, construction, manufacturing, transport and communications, wholesale trade, retail trade, finance, business and repair services, personal services, entertainment services, professional services, and public administration.

[77] We use 1999 definitions of MSAs as this set of metropolitan boundaries was the official delineations used during our time period of our analysis.

via a survey conducted in 2005, our analysis naturally begins in 2006 and terminates in 2011 after the discontinued use and reporting of 1999 MSA definitions in the IPUMS portal. The number of observations we have listed for each variable in Table 5.1 is the total number of metropolitan areas in which the data is available from each distinct dataset. As the sprawl and amenities data from Burchfield et al. (2006) and Albouy (2008) respectively are calculated at the Combined Statistical Area (CSA) level for some local metropolitan units with larger populations, we impute the same values of amenities and sprawl for all MSAs within each CBA if this is the case. Hence, our final sample in the analysis consists of 229 metropolitan areas between the years 2006 to 2011. Further details on the data used in the analysis and their source can be found in Table A-1 of Appendix A-11.

To motivate the relationship between regulatory restrictions and economic performance at the local level, we visually present some descriptive evidence of their relationship in scatterplots. Figures 5.1 and 5.2 present the static cross-sectional relationship between regulation and the log of total output and output per person across U.S. metropolitan areas respectively in the year 2006. Here, we observe that there is indeed a positive relationship with regulation and absolute output, which is consistent with the observation of many that the most economically prosperous cities also happen to be the most regulated. Conversely when examining its relationship with output per person, the two appears to be uncorrelated. This is despite the observation that median income is correlated with higher levels of regulation at the municipal level (Gyourko et al., 2008). Turning to exploring regulation's economic relationship across time, Figures 5.3 and 5.4 exhibit their relationship against the annualized growth performance of cities between the years 2006 to 2011 for output and output per person respectively. Their relationship to regulation behaves quite similarly with greater restrictiveness associated with lower rates of both output growth and output per person growth. The very different association between regulation and growth both in absolute and per capita terms warrants further investigation empirically. Finally, Figure 5.5 presents the distribution of regulatory restrictiveness spatially on a map.

5.4 Results

Table 5.2 presents the interaction specification with total output and output per capita growth as outcome variables. We report the main explanatory term of interest, regulation interacted with demand denoted as '$Reg_m \: x \: D_{mt}$', along with demand interacted with physical constraints, both geographical constraints and constraints imposed by existing settlement patterns, as well as local demand on its own respectively while the term for past years' output is not shown. As our measure of regulatory restrictions is time invariant across the sample period, the own-effects of regulation on growth outcomes are differenced out in the fixed effect specification. Regarding the OLS specification shown in Columns 1 and 2 for output per capita and output growth respectively, we observe that higher levels of local demand, proxied by local employment, are associated with high levels of output growth though it does not influence the growth of output per capita. The coefficient of the main explanatory term of interest, land-use regulation interacted with local demand, should be viewed in relation to the un-interacted demand coefficient and ought to be interpreted as regulation's impact in affecting the transmission of demand forces to local growth outcomes. Positive (negative) coefficients of the term suggest that regulations heighten (dampen) the influence of local demand to growth outcomes. The results in Columns 1 & 2, suggest that high land-use regulation contribute to higher growth in high-demand localities by magnifying local demand's influence to growth though both results are insignificant. Higher levels of spread-out development, when examined with concurrent demand forces, meaningfully binds total output growth while geographical constraints do not. As discussed earlier, measured restrictions on land use could be influenced by or be reflective of past and present local demand factors. Hence the OLS specification could be upwardly biased due to the presence of endogeneity in the specification. In Columns 3 and 4, we introduce our instrumental variable estimates where both land-use regulation and demand are instrumented for output per capita and output growth respectively. To reiterate, land-use regulation is instrumented using time-invariant naturally-occurring amenities while local demand, inferred by employment, is instrumented with a Bartik-style shift-share value. This instrumental variable specification should account for biases that arise from *both* local demand and supply factors. Both the estimated impact of land-use regulations on both total growth and growth per capita have diminished substantially compared to the OLS specifications. This is reassuring as the introduction of instruments in our specification ought to have, in part, analytically redressed the upward biasness of a naïve OLS specification. This negative influence on total economic growth as shown in Column 4 is consistent with land-use regulation acting as a binding constraint on the local economy in high-demand localities though such effects remain statistically indistinguishable from zero. Meanwhile, local demand, on its own, is still influential in raising total output growth and existing development interacted with demand still remain negatively associated with output growth, similar to the OLS specification.

At this point, we have shown that land-use regulation appears to diminish the local demand-to-growth link once intrinsic sources of biases are addressed but there is not an established, firm relationship. So far, we have yet to address an important additional indirect channel land-use regulation exert on local economic outcomes, which could have possible growth implications when positive demand shocks are present: the identified consumption response from local house price movements. As discussed earlier, local regulation, coupled with demand pressures, has demonstrably led to house price growth yet local house price movements are also shown to significantly influence local economic outcomes given their documented impacts to local consumption via housing wealth and collateral constraint channels (Campbell and Cocco, 2007; Mian et al., 2013; Mian and Sufi, 2014), particularly during the financial crisis which coincides with our period of analysis. High levels of regulation, coupled with high demand, then should also exert a positive influence on house prices and such effects could be capitalized in the local economy through consumption channels. Given these considerations, we put forward the IV specification adding local house prices as a control shown in Columns 5 and 6 of Table 5.2 for output per capita and output respectively. We observe that house prices are highly related to both growth outcomes and their inclusion in the specification, comparing Column 6 with Column 4, absorbs much of the explanatory power of the demand shifter for the total output growth specification. A crucial change that occurred is that the interaction term of regulation and demand for total output growth in Column 6 is now both negative *and* significant. After incorporating house prices, the magnitude of the interaction term of land-use regulation for total output growth more than tripled. Meanwhile, the effects to output growth per capita remain unchanged. The interpretation here is slightly more complicated. Supply-side constraints on residential housing reduce the responsiveness of total output fluctuations in the face of local demand shifters only when controlling for local house price dynamics. Land-use regulation should depress growth when paired with high demand again only *after* netting out the concurrent house price consequences from the simultaneous interaction between high demand and low supply. In addition, the differential effects to output growth and output per capita growth as shown in Columns 5 and 6 suggest that the effects to growth we document here occur at the extensive margins via in-migration and not at the intensive margins.[78] Such an effect is consistent with documented patterns of supply constraints on housing acting to reduce the employment response to positive demand shocks via in-migration (Blanchard and Katz, 1992; Saks, 2008). Our results demonstrate the importance of land-use regulation as a binding influence on growth in relation to existing pressures on demand but with an important caveat, which we will discuss in later sections.

Regulatory restrictions on land use, which restricts the use of one form of input – land – , should inevitably impact industries differentially, particularly land-intensive sectors. To identify the heterogenous effects of land-use regulation, we separately assess their impact on the economic performance of selected industries. We deploy the same empirical set-up as in Equation 1 with the same demand and supply shifters but we now examine the economic growth consequences of *specific industries* as the main outcome of interest. Here, we assess the influence of land-use regulation on the growth outcomes of the construction and the real estate industries. The industries examined conform to 2-digit NAICS classifications.[79] These industries were not selected at random but were deemed to be sectors most exposed to regulation as motivated by past research (Mayer and Sommerville, 2000; Cheshire and Hilber, 2008).

Table 5.3 presents the empirical findings of the sector-specific analysis. Columns 1 and 2 present the IV specification for the real estate and the construction industries respectively while Columns 3 and 4 display the same IV specification *including* house prices for the same respective industries. The interaction terms of the IV specification between local regulation and demand in Columns 1 and 2 for all of the sectors analyzed are all statistically indistinguishable from zero. Moving towards the IV specifications in Columns 3 and 4 in Table 5.3, we observe stark differential outcomes in the construction sector when house prices are incorporated. Initially we see a sharp negative value from the interaction term and adding in house prices causes its magnitude to nearly double in size as shown in Columns 2 and 4 respectively. When controlling for house prices, land-use regulation causes a meaningful reduction to the construction sector output growth in commensurate to the mean effect of the demand shifter. Similar to the effects found for total output growth in Column 6 of Table 5.2, land-use regulation, as shown in Column 4 of Table 5.3, constrains the growth performance of the construction sector in the face of budding demand pressures. Meanwhile, there is little to no effect from land-use restrictions to the real estate

[78] This could include affecting productivity growth or local employment rates.
[79] The NAICS codes for the construction and real estate industries in the analysis are 23 and 53 respectively.

industries with or without the inclusion of real estate prices. Our results are consistent with past literature establishing that land-use regulation reduces construction activity for residential real estate (e.g. Mayer and Sommerville, 2000; Glaeser and Ward, 2009) though our construction measure encompasses all forms of construction activity.[80] Viewing the industry as a whole, we show that high levels of regulation, in proportionate to high demand, does in fact adversely affect total industry-level output growth for construction under certain assumptions. The value of the point estimate, at more than twice the magnitude for that of total output growth in Column 6 of Table 5.3, suggest that land-use regulation disproportionally impacts sectors where land is a major input component such as the construction sector, again with an important caveat.

5.5 Discussion

Our results, taking into account both the specifications with and without house prices, suggest that land-use regulation possibly exerts two countervailing forces to the local economy; the first of which spawns an effect to local growth through house prices while the second effect, i.e. the negative impacts we've documented, reduces the responsiveness of local output growth to demand shocks through constraints on local construction and employment activity. The net effect of the two causes little to no change to growth outcomes. The first channel is land-use regulation's positive influence to local growth through house prices when demand is high. As discussed, tight restrictions on local land use, interacted with high demand, cause a house price response in metropolitan areas. Such effects are then felt through the local economy through a rise in housing net worth and a relaxation in collateral constraints, leading to greater levels of local consumption. This line of reasoning is consistent with both the literature on land-use regulation and house price growth as well as the literature on the consumption effects from house price fluctuations (Campbell and Cocco, 2007; Mian et al., 2013; Mian and Sufi, 2014). This channel is further supported by our analysis as house prices are positively and consistently associated with output growth across all specifications.

The second effect to growth from land-use restrictions is the binding adverse effect to employment growth and construction activity, findings that our results are consistent with and is supported by past work. Our specifications without house prices capture the sum of the two

[80] Residential construction comprises of approximately half of the output value of the entire construction sector. Source: Census Bureau.

channels at work with negligible net economic effects. The inclusion of house prices into the specification absorbs all house price fluctuations including those caused by supply restrictions interacted with demand i.e. the first channel. Once such factors are controlled for, the specifications with house prices, we began to tease out the negative local economic consequences that was consistent with previous studies. The rationalization of our findings according to these accounts suggests that land-use restrictions does little to impact overall local growth on net but could very much alter the composition of growth. A relaxation of zoning and planning constraints would unlikely cause growth to change in the aggregate but could lead to a shift from a consumption-driven economy fueled by housing wealth gains to one that is driven by gains in local employment in the extensive margin and construction that would not have taken place otherwise in high demand areas.

5.6 Conclusion

Tight constraints on land-use have led to house price gains in many U.S. cities with adverse consequences for housing affordability. Despite land-use restrictions being typically viewed as a constraining form of supply side regulation, many of the most tightly regulated cities have also performed well economically. To reconcile such observations, we study the joint impacts of regulatory constraints on housing and demand pressures on local growth in U.S. metropolitan areas. Using an instrumental variable interaction specification, we find no effects to local growth or to the growth of selected industries from heavy restrictions on residential housing when interacted with local demand. However, after accounting for house price dynamics, we observe that regulations dampen the transmission of local demand to the growth of total output *and* the construction sector, implying that growth is reduced from what would be predicted based purely on local demand, particularly for high-demand localities. This, we argue, can be reconciled by the simultaneous upward pressure to house prices from binding regulatory restrictions being capitalized in the local economy through a housing net worth effect in the presence of the same demand fundamentals. The combination of this phenomenon along with the negative effects to growth we documented from restrictive land use after controlling for house prices leads us to conclude that there are no effects to growth on net. Such findings still remain relevant from a policy perspective. While recent attempts to liberalize the land-use regime of various localities in the U.S. are unlikely to alter growth outcomes, it could redefine the underlying growth components reducing the growth share driven by consumption of existing residents and raising the contribution from economic activity originating from in-migration and construction endeavors.

5.7 References

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5.8 Figures and Tables

Figure 5.1: Land-use Regulation and Total Output

Figure 5.1 displays the relationship between land-use regulation and the log of total output in U.S. metropolitan areas in 2006 expressed in thousands of chained 2012 dollars. The outlier observation with the highest level of regulation is the city of Barnstable, MA. The city is omitted in the empirical analysis.

Figure 5.2: Land-use Regulation and Output Per Person

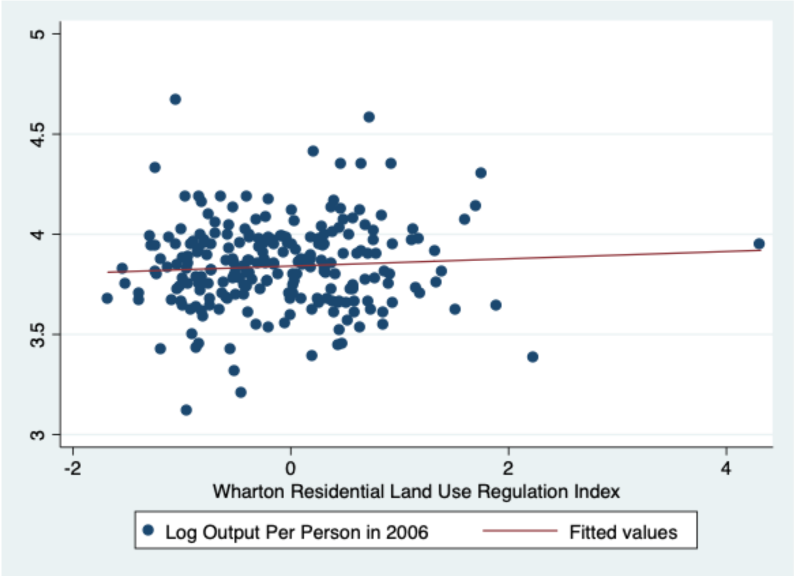

Figure 5.2 displays the relationship between land-use regulation and the log of output per person in U.S. metropolitan areas in 2006 expressed in thousands of chained 2012 dollars. The outlier observation with the highest level of regulation is the city of Barnstable, MA. The city is omitted in the empirical analysis.

Figure 5.3: Land-use Regulation and Output Growth

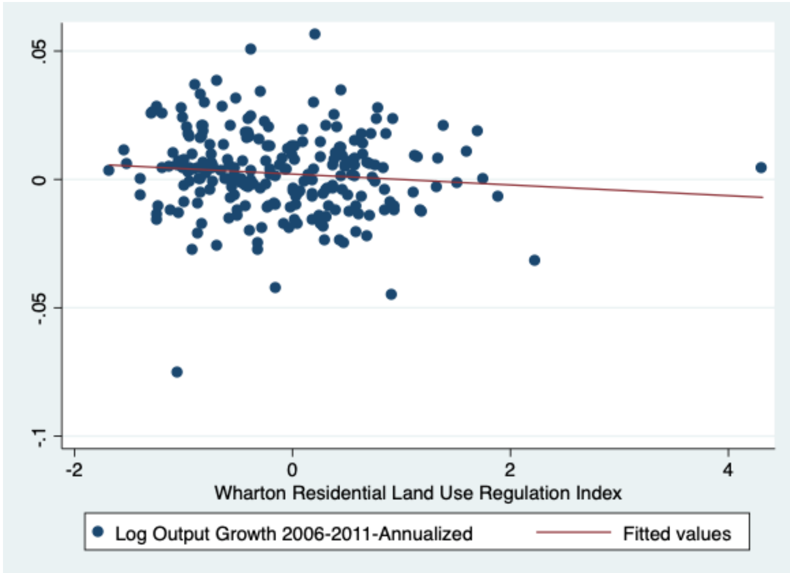

Figure 5.3 displays the relationship between land-use regulation and the annualized output growth of U.S. metropolitan areas between the years 2006 to 2011 expressed in thousands of chained 2012 dollars. The outlier observation with the highest level of regulation is the city of Barnstable, MA. The city is omitted in the empirical analysis.

Figure 5.4: Land-use Regulation and Output Per Person Growth

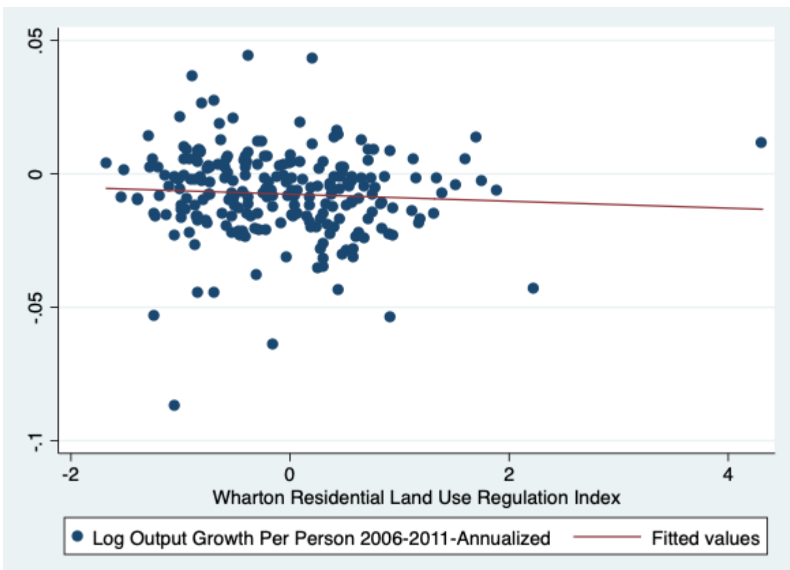

Figure 5.4 displays the relationship between land-use regulation and the annualized output growth per person in U.S. metropolitan areas between the years 2006 to 2011 expressed in thousands of chained 2012 dollars. The outlier observation with the highest level of regulation is the city of Barnstable, MA. The city is omitted in the empirical analysis.

Figure 5.5: Regulation Distribution Across the U.S.

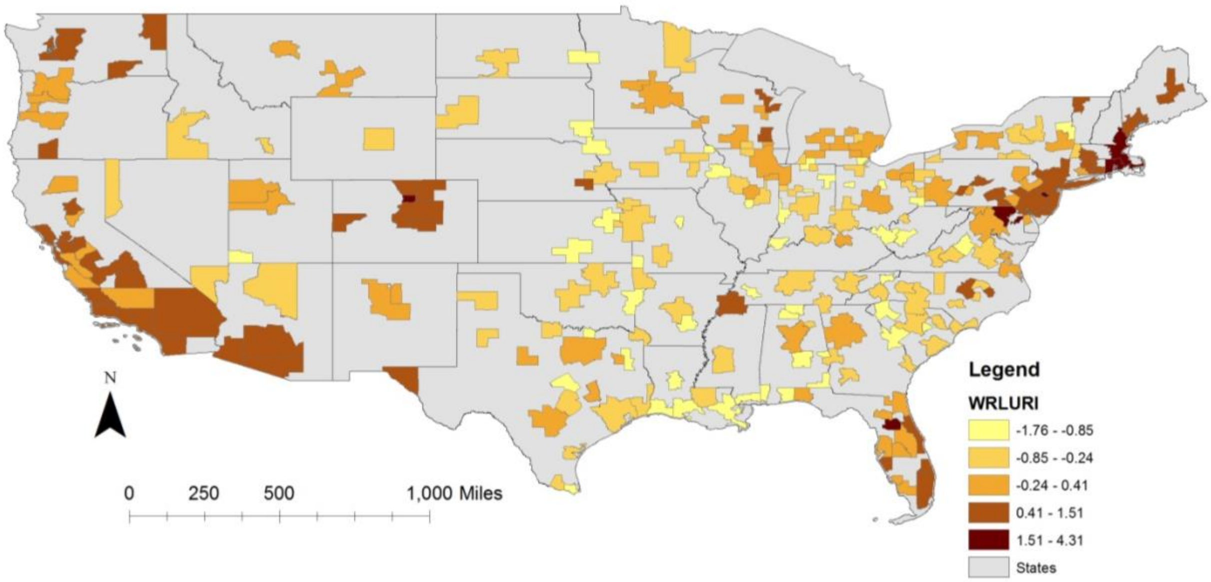

Figure 5.5 visualizes the spatial distribution of land-use regulation across U.S. metropolitan areas measured in 2006.

Table 5.1: Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Wharton Regulatory Index (WRI)	229	-.111	.739	-1.677	2.229
WRI (ln)	229	1.028	.26	.28	1.654
Unavailable Land (%)	229	25.622	20.737	1.457	77.631
Unavailable Land (ln)	229	2.853	.962	.376	4.352
Sprawl (%)	229	44.204	10.178	20.73	71.103
Sprawl (ln)	229	3.762	.237	3.032	4.264
Amenities	229	.024	.034	-.038	.141
Amenities (ln)	229	.705	.017	.674	.761
Total Output ($1000)	229	4.90e+07	8.89e+07	2830000	7.42e+08
Total Output Growth (Δ ln)	229	.031	.035	-.183	.148
Output Per Person	229	47614.46	10962.7	22581.7	107000
Output Per Person Growth (Δ ln)	229	.02	.036	-.175	.209
Output of Real Estate and Leasing ($1000)	229	5770000	1.18e+07	318000	1.01e+08
Output Growth of Real Estate and Leasing (Δ ln)	228	.069	.134	-.282	.43
Output of Construction ($1000)	229	2430000	3940000	73809	2.62e+07
Output Growth of Construction (Δ ln)	228	-.022	.183	-.268	2.426
Employment	229	565000	876000	51632.11	5920000
Employment (ln)	229	12.588	1.063	10.852	15.594
House Price	229	261000	140000	94451.52	894000
House Price (ln)	229	12.366	.443	11.456	13.703

Variables are reported at the metropolitan area level. Data is shown for the year 2006 only. Values for WRI, Sprawl and Amenities are time-invariant across the period of analysis and are measured in the years 2006, 1992 and 2000 respectively. The log of WRI and Amenity index values are obtained by first summing the index values by 3 and 2 respectively and then taking their logs. Output values are reported in thousands of chained 2012 dollars and output growth values are reported in log differences. House Prices are reported in 2012 dollars. Please refer to Appendix A-11 for further details of the variables and their source.

Table 5.2: Regulation and Output and Output Per Capita Growth

VARIABLES	(1) OLS-GDP PC	(2) OLS-GDP	(3) IV-GDP PC	(4) IV-GDP	(5) IV-GDP PC	(6) IV-GDP
Emp x Regulation (ln)	0.300	0.140	0.148	-0.150	-0.295	-0.543*
	(0.155)	(0.118)	(0.292)	(0.246)	(0.312)	(0.273)
Emp x Sprawl (ln)	-0.131	-0.294**	-0.0471	-0.236*	0.0375	-0.159
	(0.133)	(0.103)	(0.132)	(0.0957)	(0.141)	(0.0979)
Emp x Unavailable Land (ln)	-0.0304	0.00963	-0.0239	0.0283	-0.0126	0.0362
	(0.0589)	(0.0533)	(0.0646)	(0.0555)	(0.0665)	(0.0548)
Employment (ln)	-0.0116	0.196***	0.00450	0.203**	-0.0818	0.128
	(0.0530)	(0.0584)	(0.0616)	(0.0674)	(0.0596)	(0.0653)
House Price (ln)					0.0894***	0.0783***
					(0.0158)	(0.0143)
Observations	1,374	1,374	1,374	1,374	1,374	1,374
R-squared	0.512	0.551	0.278	0.294	0.294	0.300
Cluster SE	MSA	MSA	MSA	MSA	MSA	MSA
MSA & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Output	Yes	Yes	Yes	Yes	Yes	Yes
House Price	No	No	No	No	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	N/A	N/A	5.10	5.12	5.12	5.08

Columns 1 & 2 show the OLS specification while Columns 3-6 show the IV specification where both land-use regulation and employment are instrumented. The empirical specification covers data between the years 2006 to 2011. The main outcome of interest is the yearly log change in GDP per capita and the yearly log change in GDP in Columns 1, 3, and 5 and in Columns 2, 4, and 6 respectively. All variables are expressed in logs and are demeaned. The specification is estimated with metropolitan area and year fixed effects. Standard errors are clustered at the metropolitan area level. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.

Table 5.3: Regulation and the Total Output Growth of Selected Industries

VARIABLES	(1) Real Estate	(2) Construction	(3) Real Estate	(4) Construction
Emp x Regulation (ln)	0.847	-1.746	-0.646	-3.285*
	(0.652)	(1.254)	(0.657)	(1.425)
Emp x Sprawl (ln)	-0.446	-1.054	-0.135	-0.836
	(0.364)	(0.571)	(0.323)	(0.633)
Emp x Unavailable Land (ln)	0.171	0.122	0.212*	0.172
	(0.120)	(0.188)	(0.106)	(0.212)
Employment (ln)	0.575***	0.341	0.278**	0.0714
	(0.0991)	(0.240)	(0.0870)	(0.197)
House Price (ln)			0.291***	0.315**
			(0.0358)	(0.0960)
Observations	1,373	1,373	1,373	1,373
R-squared	0.458	0.231	0.495	0.225
Cluster SE	MSA	MSA	MSA	MSA
MSA & Year FE	Yes	Yes	Yes	Yes
Lagged Output	Yes	Yes	Yes	Yes
House Price	No	No	Yes	Yes
Kleibergen-Paap 1st Stage F Statistic	4.83	5.07	4.90	5.09

All specifications in Table 5.3 show the instrumental variable specification where both land-use regulation and employment are instrumented. The empirical specification covers data between the years 2006 to 2011. The main outcome of interest is the yearly log change in the output of selected industries. They include the Real Estate and Leasing and the Construction sectors as shown in Columns 1&3 and 2&4 respectively. All variables are expressed in logs and are demeaned. The specification is estimated with metropolitan area and year fixed effects. Standard errors are clustered at the metropolitan area level. Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05.

5.9 Appendix

5.9.1 Appendix A-10

Figure A: WRI Example Questions

2. Which of the following are required to approve zoning changes, and by what vote?

	Yes	Yes, by simple majority	Yes, by more than simple majority	No
- Local Planning commission				
- Local Zoning Board				
- Local Council, Managers, Commissioners				
- County Board of Commissioners				
- County Zoning Board				
- Environmental Review Board				

5. Does your community place annual limits on the total allowable:

	Yes	No
- No. of building permits – single family?		
- No. of building permits – multi-family?		
- No. of residential units authorized for construction – single family?		
- No. of residential units authorized for construction – multi-family?		
- No. of multi-family dwellings?		
- No. of units in multi-family dwellings?		

10. What is the current length of time required to complete the review of residential projects in your community?

For single-family units: _______ months For multi-family units: _______ months

12. What is the typical amount of time between application for rezoning and issuance of a building permit for development of:

	Less than 3 mos.	3 to 6 mos.	7 to 12 mos.	13 to 24 mos.	If above 24, How long?
- Less than 50 single family units					
- 50 or more single family units					
- Multi-family units					

Fig. 4. Example questions from the Wharton Residential Land Use Regulation Index survey.

Source:(Paciorek, 2013, pp. 17; Gyourko et al., 2008)

5.9.2 Appendix A-11

Table A-1: Data Description and Sources

Variable	Description	Source
Wharton Regulatory Index	Index measuring the degree of local regulatory constraints on residential development.	Saiz (2010) & Gyourko et al. (2008)
Unavailable Land	Share of land with bodies of water & land with slopes above 15 degrees within 50 km radius of central city	Saiz (2010)
Sprawl	Percentage of undeveloped land in the square kilometer surrounding an average residential development	Burchfield et al. (2006)
Urban Amenities	Composite indicator comprising of natural amenities including heating and cooling degree days per year, sunshine, coastal proximity, and the average slope of the land	Albouy (2008)
Growth	Difference of yearly GDP Output	BEA
Employment	Metropolitan Average of Self-Reported Employment Status Interacted by Census Population Estimates	ACS & CB via IPUMS (Ruggles et al. 2021) and NBER
House Prices	Metropolitan Average of Self-Reported House Prices	ACS & CB via IPUMS (Ruggles et al., 2021)