IT and Urban Polarization*

Jan Eeckhout† Christoph Hedtrich‡ Roberto Pinheiro§

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Abstract

We show that differential IT investment across cities has been a key driver of job and wage polarization since the 1990s. Using a novel data set, we establish two stylized facts: IT investment is highest in firms in large and expensive cities, and the decline in routine cognitive occupations is most prevalent in large and expensive cities. To explain these facts, we propose a model mechanism where the substitution of routine workers by IT leads to higher IT adoption in large cities due to a higher cost of living and higher wages. We estimate the spatial equilibrium model to trace out the effects of IT on the labor market between 1990 and 2015. The decline in IT prices alone accounts for about 30 percent of the stronger displacement of routine cognitive jobs in expensive locations.

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†UPF Barcelona (ICREA-BSE-CREI), jan.eeckhout@upf.edu
‡Uppsala University, christoph.hedtrich@nek.uu.se
§Federal Reserve Bank of Cleveland, Roberto.Pinheiro@clev.frb.org

1 Introduction

Polarization in the labor market is one of the main forces behind the rise in wage inequality (see Acemoglu and Autor (2011) and Cortes et al. (2017)). With the advent of the information age, new technologies tend to make workers more productive, but they affect different workers differently. In particular, the labor-saving investment has the highest return where information technology (IT) substitutes routine tasks. Those routine tasks are disproportionately performed by workers earning wages in the middle of the distribution, and as a result, the displacement of these jobs leads to polarization of the earnings distribution. Moreover, there is a marked geographical dimension to polarization (see Autor (2019), Autor and Dorn (2013)), with strong variation in polarization across metropolitan areas.

Yet, to date, little is known about the mechanism that links investment in IT and job displacement and how this mechanism explains the geographical variation. In this paper we make two contributions. First, we analyze a novel data set and we document two new stylized facts: 1. IT investment is highest in large, expensive cities; 2. The decline in routine cognitive occupations is largest in large, expensive cities. We obtain these two facts from analyzing micro-data on IT usage at the establishment level and US Census data on employment. We show that these empirical results are robust and hold under many different specifications, most notably after controlling for *firm* fixed effects and headquarter location.

Second, we propose an equilibrium mechanism that can rationalize these facts and that explains why polarization is a phenomenon with a strong urban component. The main insight is that the composition of the production factors that firms choose varies by geography: workers must be compensated for *local* housing prices, whereas IT is a highly tradable good that can be bought at similar prices *everywhere*. As a result, labor and IT demand varies significantly with cities' cost of living. Because across locations, housing prices comove with labor productivity and wages, it is beneficial for firms to use IT more intensively in expensive cities. Consequently, more productive areas are the ones prone to replace routine tasks with IT because those routine tasks disproportionately drive up the cost of labor.

The focus in our empirical analysis is on the distribution of employment and our stylized facts document the effect of IT investment on the displacement of routine cognitive workers across geographical locations. At the same time, the technological change that is at the origin of the change in the distribution has general equilibrium effects on wages. In our empirical analysis, we document in detail the pattern of wage inequality. We show the evolution of the relative wages of cognitive occupations across cities. We find that the wage premium of non-routine over routine cognitive occupations increased, and this increase has been even larger in expensive locations.

With these facts about the distribution of employment and wages in mind, we build an equilibrium model of production in cities with heterogeneous workers who optimally choose their location and occupation, given their exogenous abilities and their idiosyncratic taste for different locations. Moreover, representative firms in each city choose their optimal input combination given the region's total factor productivity (TFP), the differential cost of production inputs, and the degree of complementarity between each occupation and IT. Furthermore, labor and IT differ in their tradability. Labor must be provided locally; as a result, wages are determined by local labor market conditions. Instead, each city is seen as a small open economy in the market for IT. In other words, our model combines elements from Roy (1951), Rosen (1979), Roback (1982), and Krusell et al. (2000).

First, we derive analytical results for a simplified version of the model. This gives us crisp insights into the workings of the economic mechanism. We show that the impact of the cost of living on the distribution of occupations across space depends crucially on the elasticity of substitution between labor and IT. Labor in occupations that feature a high elasticity of substitution are reallocated towards cheaper cities when IT productivity rises. By contrast, occupations that are more complementary sort into expensive cities. Now in turn, the cost of living is an equilibrium outcome. We show that in equilibrium, more productive cities have higher housing prices, and we derive conditions under which there is more investment in IT in cities with higher TFP. This then allows us to establish that more productive cities are larger in population size and that there is spatial sorting by occupations consistent with the stylized facts.

Second, we estimate the model parameters for the full model – in particular the productivity parameters for the different routine and non-routine occupations as well as the parameters governing the distribution of amenities and housing supply – matching city- and occupation-level moments of the wage and employment distribution. We find that IT has a prominent role in explaining recent employment and wage trends across cities. A counterfactual exercise where we simulate a fall in IT prices by 65 percent – corresponding to a similar change in the data between 1990 and 2015 – leads to both a fall in employment in routine cognitive jobs and a rise in non-routine cognitive jobs. Further, the wage premium of non-routine cognitive over routine cognitive occupations increases. The main result of the model simulation is the strong urban component of polarization: the employment share of routine cognitive occupations falls substantially more in expensive locations. The fall of IT prices alone accounts for about 30 percent of the stronger displacement of routine cognitive jobs in expensive locations. Similarly, the wage gap between routine and non-routine cognitive jobs widens even more in expensive locations. Overall the results indicate a strong role for IT in the displacement of routine cognitive employment and a rise in non-routine cognitive employment and the accompanying polarization of earnings across jobs and cities.

Our results highlight the importance of the housing price mechanism in explaining inequality patterns in the data. While the geographical variation of polarization has been pointed out before, our findings establish that local housing prices play a key role. The model mechanism is key in gaining this insight because housing prices cannot be used as an instrument as prices are determined in equilibrium and therefore do not satisfy the exclusion restriction. Our estimates bestow a new, crucial ingredient in the mechanism behind polarization that was hitherto absent in the literature.

Our empirical analysis focuses on cognitive occupations. While we see similar patterns of polarization in manual occupations that is driven by investment in automation, it is likely not driven solely by IT. Instead, automation technologies in manufacturing consist predominantly of industrial robots, for which we have no data. In addition, in contrast to robots, general IT has almost no local space requirement. Given the nature of our data, we analyze workers in cognitive jobs, as they use IT more intensively.[1]

There are of course alternative explanations for the observed pattern of skill and wage inequality that we analyze. The most prominent in the literature are the mechanisms driven by agglomeration externalities (Baum-Snow et al., 2018; Rossi-Hansberg et al., 2019), skill-biased technological change (Rubinton, 2022; Eckert et al., 2021), amenities, and home ownership (Parkhomenko, 2022). Unfortunately, we lack the data to run a horse race between those alternative explanations and our mechanism.[2] Nonetheless, in the empirical section, we address these alternative explanations whenever possible, by including explanatory variables that may serve as proxy for these channels. For example, we include the skill ratio, the initial employment shares by industry and occupation, offshorability, and the housing supply elasticities in the regressions that measure the change in the routine-cognitive share to account for the mechanisms in Autor and Dorn (2013); Beaudry et al. (2010); Parkhomenko (2022). We also include city size as a proxy for agglomeration externalities and find that our results are preserved. In the quantitative exercise, we isolate the role of IT prices from potential agglomeration externalities (Baum-Snow et al., 2018; Rossi-Hansberg et al., 2019).

Related Literature. Our paper builds on a large literature on the polarization of the labor market and the disappearing routine jobs, for example, Autor and Dorn (2013), Goos et al. (2014), Cortes et al. (2017), and Acemoglu and Autor (2011). Much of the focus of this literature is on technological change as the main driver of polarization. We embrace this technological explanation but focus on the role of capital investment. The notion that capital investment affects different skilled workers is of course not new. Krusell et al. (2000) were the first to argue that the college premium has risen so much because technological investment affects the high skilled more than the low skilled. The drop in the cost of such new technologies then further widens the gap between skilled and unskilled workers. We rely on a similar mechanism to explain the polarization of the labor market.

In addition to the role of capital investment, our analysis focuses on differential technology adoption across cities. Beaudry et al. (2010) show that technology adoption – measured by PCs

[1]See Section 4.3 for a measure of IT usage across job categories. The space requirement of manufacturing establishments may be a factor that pushed manufacturing activities to rural and less dense areas (see Holmes and Stevens (2004)'s table 10). Consequently, the investment in ICT technology and other types of technology – for example industrial robots – have quite distinct geographical component. Comparing our IT data and the IFR data matched regionally by industry concentration (as presented by Brookings here), we obtain a correlation of just 0.26 at the MSA level. A clear reason for that is the concentration of industrial robots in manufacturing, in particular the automotive industry. As pointed out by the Brookings report, about half of the industrial robots in use in 2017 were in the automotive industry.

[2]While we have IT data over time, it is not comparable. In the early period, we have the list of computers, but not in the later period, and in the later period we have data on expenditure on IT but not in the early period.

per worker – has occurred first in areas with a relatively high supply of skill (or with a low relative price of skill). They also show that these areas experienced the greatest increase in the return to education. Our analysis, while controlling for the relative supply of high skill workers in the MSA, highlights the importance of local prices in the sorting of workers and activities across space, which is mostly missing from the analysis by Beaudry et al. (2010). Moreover, by allowing more than two types of workers, our framework is better suited to address the issues of job polarization and the "disappearing middle" of the income distribution.

We also analyze the evolution of wage inequality across cities, both empirically and in the model. Baum-Snow and Pavan (2013) and Baum-Snow et al. (2018) document that wage inequality rose more in large cities in the US between 1980 and 2007, suggesting that the forces driving inequality have an urban bias. Our paper provides a mechanism for this finding: the endogenously more intensive adoption of IT in expensive locations. Our empirical findings go further by focusing on the evolution of inequality across different tasks. Baum-Snow et al. (2018) estimate production functions and find evidence for capital-skill complementarity, but also skill bias in agglomeration economies of technical change. Our paper instead focuses on the spatial implications of technological change in an equilibrium system of cities and highlights that the adoption of IT can explain, at least in part, the skill bias in agglomeration economies. Further, our paper documents results using novel data on IT usage across the whole economy and not just capital data from the manufacturing sector.

Kleinman (2022) also analyzes technological change and geographic inequality, but he zooms in on the role of multi-region service firms. He finds that larger firms operate in more locations and pay higher wages in spatially-concentrated headquarters. In a model with wage-setting power, he shows that wage inequality is tightly linked to the frictions for large firms to expand geographically. His mechanism can account for rising inequality across establishments, and higher inequality and segregation across space. Unlike our model, Kleinman (2022)'s mechanism does not exhibit polarization of occupations driven by falling costs in investment in labor-saving IT. Consequently, his model cannot address the polarization pattern that we observe in the data.

There is an extensive literature documenting geographical patterns of occupations that are related to our results. Rubinton (2022) finds that the adoption of IT is higher in larger cities. She uses data from the Annual Capital Expenditures Survey, thus complementing our findings. The focus of her paper is on the gap in wages between low- and high-skilled workers and business dynamism. In contrast, here the focus is on the role of technology in the polarization of employment and wages. Rossi-Hansberg et al. (2019) study cognitive hubs and find, as we do, that non-routine occupations are disproportionately represented in large cities. They use different data and propose an interesting mechanism that is based on a flexible technology specification that exhibits externalities, which leads to inefficient equilibrium allocations. They find crisp predictions regarding optimal policy, in an approach that is complementary to ours.

In a study of the role of technological change in regional convergence in the US, Giannone (2017) finds that skill-biased technological change can explain a substantial share of the decline in regional convergence across cities in the US. A key difference is our focus on the role of technology behind the evolution of wages and employment and the endogenous nature of adoption of said technology. Cerina et al. (2022) calibrate a spatial equilibrium model and find, based on the model, that skill-biased technological change is important in explaining employment patterns across space. While closely related, we focus instead on the adoption of technology in space, which has the crucial distinction that it is not measured as a residual. As such, we provide an explanation for why skill-biased technological change is uneven in space. Finally, Davis et al. (2020) provide closely related and complementary theory results regarding the sorting of workers. Further, they document related patterns of the sorting of workers across cities in France suggesting that our results may extend beyond the US economy. However, they do not use direct evidence on technology to determine its role for their findings.

The paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical results and the two stylized facts. Section 4 contains the equilibrium mechanism that rationalizes the facts based on a general equilibrium model. The section contains the setup of the general model, a series of analytical results for a simplified version of the model, and the estimation of the full model. We use the estimated model to trace out the effects of IT on the labor market within and across cities under counterfactual scenarios. Finally, we make some concluding remarks in Section 5. All proofs are presented in the Appendix.

2 Data Sources and Measurement

Data on Workers. Our main data source is the Census public use microdata. We use the 5% samples for 1980, 1990, and 2000 and for 2014-2016 we combine the American Community Survey (ACS) yearly files. From these files, we construct labor force and price information at the metropolitan statistical area (MSA) level.[3] For each year we then construct information on the labor force, earnings, and the local price level in each MSA. We focus our attention to full-time, full-year workers aged 25-54.[4]

Our variable for the price at the MSA level is a simple price index including both consumption goods – which sell at the same price across different locations – and housing, which is priced

[3]The definition of a MSA we use is the Census Beaureau's 2000 combined metropolitan statistical areas (CMSA) for all MSAs that are part of an CMSA or otherwise the MSA itself. For simplicity, we will refer to this definition as MSA from now on. We follow the same procedure as Baum-Snow and Pavan (2013) in order to match the Census Beaureau's public use microdata area (PUMA) of each census sample to the 2000 Census Metropolitan Area definitions. The census data restricts us to consider only MSAs that are sufficiently large, as they are otherwise not identifiable due to the minimal size of a PUMA.

[4]In particular, we restrict our sample to workers who report working at least 40 weeks, 35 usual hours per week and who earn at least 75 percent of the federal minimum wage in each year. Our earnings measure is the log hourly wage calculated by subtracting log weeks times usual hours worked. Since the information on weeks worked in ACS 2013-2015 is presented in intervals, we use the same interval mid-points in order to calculate the usual hours worked for the census samples. Finally, to maintain comparability with the census data, we shift the wage distribution in each of the ACS sample years to have the same median as that for the 2015 sample. Similarly, we adjust all earnings data to reflect values in 2000 US dollars.

differently in each MSA. Based on a hedonic regression using rental data and building characteristics, we calculate the difference in housing values across cities. In particular, we follow the procedure presented by Eeckhout et al. (2014), while applying it to MSAs and using 1980 Census data in most cases.[5] In large parts of our empirical analysis we focus on the occupational composition of MSAs. To do so, we aggregate the census occupations into broad groups based on their task content as in Cortes et al. (2014). Table A-1 shows the classification into groups by task components and the corresponding titles of occupation groups in the Census 2010 Occupation Classification system. We differentiate jobs along two dimensions: i) whether jobs are intensive in non-routine vs. routine tasks to captures the exposure to potential automation, and ii) we differentiate whether jobs are either manual skill or cognitive skill intensive to capture the particular importance of IT for cognitive jobs. Table A-2 shows the share of employment by occupation group for 1990 and 2015. In Table A-3 we show employment by occupation separately for low- and high-rent cities. Employment shifted away from routine to non-routine jobs, and did so unevenly across space. We discuss the spatial pattern in detail below.

Data on IT. The technology data come from the Ci Technology Database, produced by the Aberdeen Group (formerly known as Harte-Hanks). The data have detailed hardware and software information for over 200,000 sites in 2015[6] including not only installed capacity but also expected future expenses in technology. Their data also include detailed geographical location for the interviewed sites, as well as aggregation to the firm level. Finally, they also collect some basic information about the sites, such as detailed industry code, number of employees, and total revenue.

We consider several measures of investment in technology. Initially, we consider a broad measure of investment in technology: the total IT budget per worker. While this measure may overstate the investment in technology made to either boost the productivity or replace a given set of workers, it has several advantages. First, this measure is available for all the establishments in our sample. Second, the portion of our database that includes IT budget information covers a significant fraction of the employed labor force as well as establishments, when compared to other standard databases such as the National Establishment Time-Series (NETS) and the County Business Pattern (CBP). For example, compared to NETS our sample covers on average 52 percent of the MSA's employed labor force. An even larger share of the employed labor force is covered when compared to the CBP (73 percent). We find that there is nearly full geographical coverage, with only very few MSAs missing.[7] In fact, the missing MSAs are due to the matching procedure of the census PUMA to the 2000 census metropolitan area definitions as described by Baum-Snow and Pavan (2013). Finally, we compare the distribution of IT investment across industries generated by Aberdeen to the same

[5]In contrast, Eeckhout et al. (2014) focuses on CBSAs and 2009 ACS data. For more details, please see Eeckhout et al. (2014)'s Appendix B.

[6]In fact, the overall sample is significantly larger than 200,000, but we are restricting the sample to the plants and sites for which we have detailed software information.

[7]See Figure A-2 in the Appendix and Figure OA-1 in the Online Appendix for the geographical dispersion of the IT budget per worker in 2015 relative to CBP and NETS, respectively.

distribution based on BEA's 2015 investment table at the detailed estimates by industry and by type of assets. While the distributions don't line up perfectly – in particular, the definitions of IT budget and fixed investment differ – the aggregates generated by Aberdeen are highly correlated with the BEA aggregates (north of 0.7). Detailed descriptive statistics about the IT data are provided in the Appendix Sections A, B, and C.

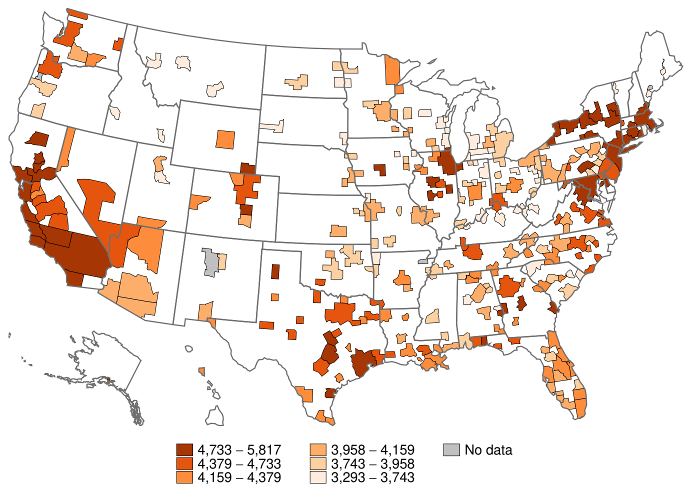


Figure 1: Avg. IT budget per worker

We also focus on measures that target the degree of complementarity between a group of occupations and technology. In particular, we use the adoption of enterprise resource planning (ERP) software in order to measure the establishments' intent in automating routine cognitive tasks. As pointed out by Bloom et al. (2014), ERP software systems integrate several data sources and processes of an organization into a unified system, reducing the need for clerical and low-level white collar workers. We consider ERPs that help in managing the following areas: Accounting, Human Resources, Customer & Sales Force, Collaborative and Integration, Supply Chain Management, as well as bundle software like the ones produced by SAP, which are usually called enterprise applications.

The main benefit of using ERP is that it is a clear measure of an establishment's intent in automating certain tasks. In this sense, the measure of ERP software is quite distinct from aggregate measures such as IT budget and other general purpose technologies, such as the adoption of personal computers. The key drawbacks are: first, there is a significant reduction in establishment coverage. Our information on ERP adoption covers on average only 20 percent of workers and 1 percent of establishments in the MSA, compared to NETS (see Online Appendix Table OA-1). Similarly, our ERP sample covers on average only 25 percent of workers and 2 percent of establishments in the MSA, compared to the CBP (see Appendix Table A-5). Second, we need to focus on coarser measures of technology adoption. Our leading measure of ERP adoption is the fraction of establishments in the MSAs that adopted ERP software. This measure does not capture the intensive margin of ERP adoption.[8] Due to the drawbacks of the ERP measure, we focus our analysis on the IT budget per worker in Section 3. However, we present the results for ERP measures in Appendix Section D. While results are understandably weaker for ERP – due to smaller sample size – they are qualitatively similar to the ones presented in Section 3.

Data on Metropolitan Areas' Characteristics. In order to control for metropolitan area characteristics, we gather information on housing supply elasticity, natural amenities, and industry composition in the MSA. Our key measure for the housing supply elasticity is based on Saiz (2010). This measure takes into account both land use restrictions and geographical restrictions on building in different areas.[9]

We control for amenities using the climate and geographical measures presented in Appendix B.4 of Albouy (2012). In particular, we focus on the measures that capture heating and cooling degree days (annual); average sunshine as a percentage of possible; average slope of the land in the metropolitan area; and average distance to the closest coastline.[10]

We follow Beaudry et al. (2010) and include controls that reflect a city's employment mix across 12 industry groups in 1980 in order to control for the metropolitan areas' industry composition.[11]

3 Empirical Evidence

In this section we document the main findings regarding urban polarization. In the first subsection, we report the evidence on technology adoption and job polarization by city housing cost. In the second subsection, we focus on the empirical implications for wage inequality.

[8]For example, consider two establishments, A and B, that adopt ERP software to different degrees. Establishment A adopts a relatively simple accounting software that may replace the work of a few accounting assistants. Differently, establishment B adopts an integrated ERP software system that allows it to automate several processes within the firm – sales, HR, inventory, accounting, etc. Both establishments would be classified as "adopters" and contribute the same to our leading measure. Consequently, our leading measure will be biased towards finding no effect.

[9]In previous versions, we presented robustness considering two additional measures. The Wharton Residential Land Use Regulation Index (WRLURI), based on work by Gyourko et al. (2008), which takes into account building regulations. Ganong and Shoag (2017)'s Land regulation index, which is based on the number of state supreme and appellate court cases containing the phrase "land use" over time.

[10]In previous versions, we considered natural amenities coming from the US Department of Agriculture (USDA). In particular, we focused on the following measures: mean temperature for January (1941-1970); mean temperature for July (1941-1970); mean hours of sunlight for January (1941-1970); ln(% of water area); mean relative humidity for July (1941-1970). Results were qualitatively similar.

[11]In particular, we control for the share of employment in industry categories that correspond roughly to one-digit SICs (public sector is the excluded category): Agriculture and Mining; Construction; Non-durable Manufacturing; Durable Manufacturing; Transportation and Utilities; Wholesale; Retail; Finance, Insurance, and Real Estate; Business and Repair Services; Other Low-Skill Services; Entertainment; Professional Services. To calculate this share, we gather information on employment across industry sectors within MSAs using the 1980 County Business Patterns (CBP).

3.1 Technology Adoption and Job Polarization by City Housing Cost

In describing the evidence on the adoption of ICT and the occupational composition of cities, we report two main findings: (1) locations with higher housing costs adopt ICT at higher rates; and (2) locations with higher housing costs see a decreasing share of their workforce employed in routine-cognitive occupations, whose tasks are being replaced by ICT.

Fact 1. Stronger IT Adoption in Expensive Cities. Figure 2 visualizes the positive correlation between local rental prices and the average IT budget per worker. Mere inspection shows that the magnitude of the change in IT spending as the rent index changes is sizable. Furthermore, Table 1 shows the results for MSA-level linear regression models of the log of the average IT budget per worker, adjusted for plant employment interacted with three-digit SIC industries, following Beaudry et al. (2010) and Doms and Lewis (2006).[12]

The regression results provide support for the hypothesis that IT expenditure per worker is increasing in the cost of housing. The elasticity is highly significant and its value barely changes under different regression specifications. The MSA's rental price index in 1980 helps explain the variation in IT budget per worker across MSAs, even after controlling for the presence of natural amenities, housing supply elasticity, and industry composition.[13]

In specification (1), places with a local price index one standard deviation higher than the average (an increase of 25 percent in the 1980 local price index) is associated with an increase of \$77.44 in the MSA's average IT budget per worker. This magnitude corresponds to an increase of 2.84 percent in the average IT budget per worker. Specification (2) introduces controls for MSA characteristics, including natural amenities and industry mix controls. In this case, places with a local price index one standard deviation higher than the average (an increase of 25 percent in the 1980 local price index) are associated with an increase of \$80.25 in the MSA's average IT budget per

[12] We follow Beaudry et al. (2010) and Doms and Lewis (2006) in constructing a measure of (the log of) IT investment per capita for MSA $j \in \{1, ..., J\}$ by running the following regression:

$$\log\left(\frac{\text{IT Investment}}{\text{Total Employees}}_i\right) = \alpha + \sum_{j=1}^{J} \theta_j \mathbf{I}(i,j) + \varphi_i(k,l) + \varepsilon_i$$

where $\mathbf{I}(i,j)$ is an indicator function which is equal to 1 if establishment i is located in MSA j and zero otherwise. $\varphi_i(k,l)$ is establishment i's size category k and industry l's fixed effect. Following Beaudry et al. (2010), we use 3-digit 1987 SIC codes as our industry categories − results are robust by substituting 1987 SIC codes with 2012 NAICS codes. We consider 8 size categories based on employment size (5 to 9, 10 to 19, 20 to 49, 50 to 99, 100 to 249, 250 to 499, 500 to 999, and more than 1,000 employees). We ran the results for a unweighted regression as well as a weighted regression using County Business Pattern weights, with similar results in both cases. Our measure for the log of IT investment per capita for MSA j is then constructed as:

$$\log(IT_j) = \widehat{\alpha} + \widehat{\theta}_j.$$

[13] As pointed out by Beaudry et al. (2010), in this case the industry mix controls are on top of the detailed industry adjustment already preformed on the dependent variable (three-digit SIC × establishment size). The industry mix controls therefore capture any additional indirect or "spillover" effects of industry mix in the IT regressions.

worker, corresponding to a 2.94 percent increase in the average IT budget per worker. Specifications (3) and (4) find a statistically significant correlation between the MSA's share of routine cognitive jobs in 1980 and the area's ratio of college equivalents to non-college equivalents with average IT budget per worker in 2015. These results corroborate findings presented by Autor and Dorn (2013) and Beaudry et al. (2010), respectively. However, as we include all controls presented in specifications (1)-(4) together in specification (5), the MSA's share of routine cognitive jobs in 1980 and the area's ratio of college equivalents to non-college equivalents lose statistical significance.

Instead, the impact of local rent prices shows only a minor change in statistical significance between specifications (1) and (5). Specification (6) controls for the MSA's average degree of offshorability of local jobs in 1980 – using the task offshorability index presented by Autor and Dorn (2013). We find again that the impact of local housing prices is robust to the addition of the controls. Finally, in Appendix Table A-19 we introduce MSA employment size in 1980 as control.[14] Results indicate that, while by itself the MSA size is positively correlated with average IT budget per worker, the control loses significance once we introduce the local price index as a control. As a result, the mechanism is likely mediated by the cost of living, and not exclusively agglomeration externalities.

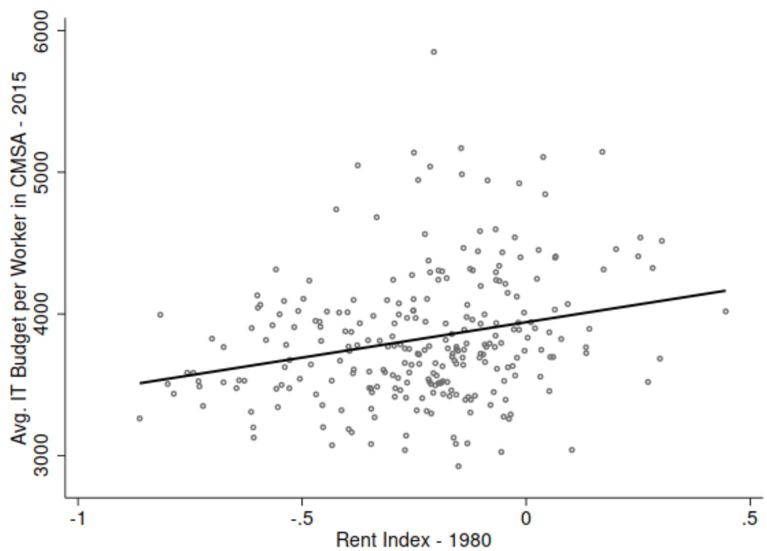


Figure 2: Avg. IT per worker vs local price level

Results from Table 2 highlight the importance of local prices for the establishment's IT budget per employee, even after controlling for establishment characteristics and industry fixed effects. In fact, from specification (3), we observe establishments in places with a local price index one standard deviation higher than the average (an increase of 21.4 percent in the local price index) are associated with an increase in the establishment's average IT budget per worker of about \$66.90. This magnitude corresponds to an increase of 2.4 percent in the average IT budget per worker. While this effect seems small, we must keep in mind that we are already controlling for

[14]The two variables are positively correlated, with a correlation coefficient around 0.4.

Table 1: IT budget per worker – 2015

	log(IT)					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.125***	0.132***			0.108**	0.110**
	(0.021)	(0.040)			(0.044)	(0.043)
MSA RC share 1980			0.594**		0.406	0.466
			(0.291)		(0.313)	(0.338)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0579**	0.012	0.012
				(0.0269)	(0.030)	(0.030)
MSA Offshorability 1980						-0.077
						(0.106)
Housing supply elasticity		0.003	0.000	0.0004	0.003	0.003
		(0.004)	(0.004)	(0.0038)	(0.004)	(0.004)
Amenities	No	Yes	Yes	Yes	Yes	Yes
MSA's Industry Mix Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	35.38	15.63	14.01	14.92	15.08	14.42
Adj. R^2	0.097	0.377	0.360	0.359	0.380	0.379
MSAs	218	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the metro area, adjusted for plant employment interacted with three-digit SIC industry. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

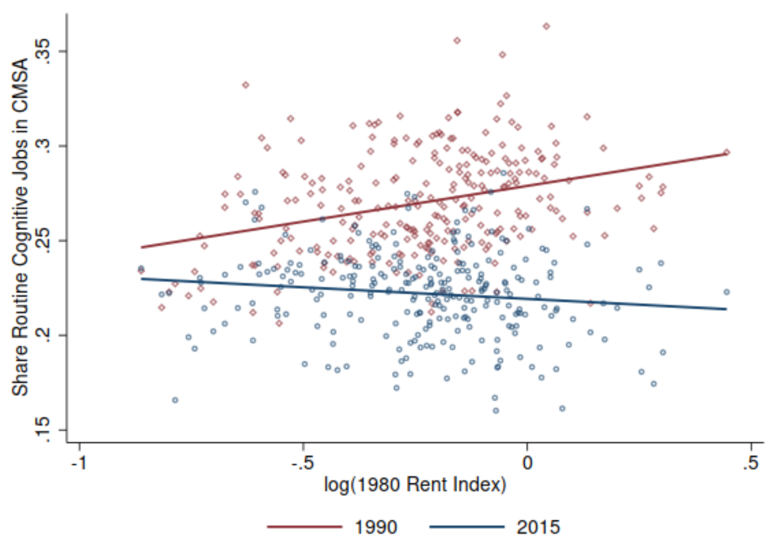


Figure 3: Routine-Cognitive share of employment: 1990 vs. 2015

industry-fixed effects, as well as establishment's size and revenue and MSA's natural amenities, labor force composition, and industry mix. Moreover, notice that the coefficient of the local price index on IT budget per worker does not vary significantly across the different specifications presented in

Table 2: IT Investment by Establishment

	log(IT)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980	0.434***	0.322***	0.112***			0.100***	0.096***
	(0.058)	(0.042)	(0.025)			(0.030)	(0.030)
MSA RC share 1980				0.002		0.000	-0.000
				(0.002)		(0.002)	(0.002)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.055***	0.019	0.017
					(0.019)	(0.021)	(0.021)
MSA Offshorability 1980							0.076
							(0.063)
log(Site's Size)		-0.003	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***
		(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Site's Revenue)		2.839***	2.557***	2.558***	2.558***	2.557***	2.557***
		(0.070)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Headquarters dummy		-0.046***	0.000	0.001	0.001	0.000	0.000
		(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Housing Elasticity			-0.003	-0.008*	-0.006	-0.003	-0.004
			(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	56.16	596.77	19,484.29	20,340.62	16,888.61	20,074.25	19,548.24
Adj. R^2	0.0089	0.4216	0.7139	0.7138	0.7138	0.7139	0.7139
No. of Sites	267,180	261,488	247,933	247,933	247,933	247,933	247,933
No. of Firms	131,400	131,333	125,002	125,002	125,002	125,002	125,002
No. of MSAs	262	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Each observation (an establishment) is weighted by the probability weight from a match between the Aberdeen data and the 2015 County Business Patterns. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are two-digit SIC dummies. We cluster standard errors at the MSA level. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2, once we introduce the initial controls in specification (3). Furthermore, the coefficients of the share of routine cognitive workers in 1980, MSA's average degree of offshorability of the local jobs in 1980, and MSA's ratio of college equivalent workers are all statistically insignificant, once we control for MSA's rent index (see Specifications (6) and (7)).

In Appendix Table A-15, we introduce firm fixed effects. Notice that in this case, our sample is ultimately restricted to multi-establishment firms with establishments in different MSAs. Nevertheless, our results are preserved even with the inclusion of fixed effects, showing that within the same firm, establishment in more expensive MSAs invest proportionately more in technology.

Tables A-20 and A-21 in the Appendix add MSA employment size as a control for the cases with and without firm fixed effects. In both cases, results for the local price index are preserved. Differently, MSA employment size is statistically insignificant after controlling for local rental prices in the case without firm fixed effects, while having a small positive impact in the case with fixed effects. In line with the proposed mechanism, these results show that IT investment is higher in expensive cities, even when compared to similarly sized, cheaper cities.[15]

Finally, since establishment size and establishment revenue may be correlated with city rents and city size, in appendix tables A-22, A-23, A-24, and A-25, we replicate our analysis while omitting log(Site's Size) and log(Site's Revenue) as controls. Results are again robust in terms of statistical significance and a bit stronger in terms of magnitudes of the coefficients of the variables of interest.

Fact 2. Routine Cognitive Occupations Decline Faster in Expensive Cities. We now turn to the second result: high-cost locations feature a stronger decline in the share of workers in routine occupations. Their tasks are expected to be the most exposed to automation from the introduction of ICT. We graphically show the changing relationship between the local price index and the share of the employed labor force in routine cognitive jobs in Figure 3. In 1990 the relationship was positive and statistically significant, while in 2015 it was negative and statistically significant.

In documenting this fact, in Table 3 we control for potential alternative explanations that have been put forward in the literature, such skill-biased technological change, amenities, and home ownership (Rubinton, 2022; Eckert et al., 2021; Baum-Snow et al., 2018; Parkhomenko, 2022; Autor and Dorn, 2013; Beaudry et al., 2010). In particular, we introduce as controls variables known to proxy for these alternative explanations, such as the skill ratio, the initial employment shares, offshorability, and the housing supply elasticities.

We use 1980 as the pre-technology period in order to construct the control variables and compare it to the occupational composition in the period 1990–2015. Our focus on such a long span of time is motivated by the fact that in the model, we compare steady-state predictions and ignore short-term dynamics. Furthermore, the national trend shows a decline in the share of routine cognitive jobs starting in the late 1980s.

Table 3 presents the results of linear regressions of the change in the MSA's share of routine cognitive occupations between 1990 and 2015. Specification (1) indicates that places with a local price index one standard deviation higher than the average in 1980 (an increase of 25.3 percent in the local price index) are associated with a 1 percentage point larger drop in the routine cognitive share over 1990-2015. Thus, the most expensive places have about a 5 percentage point larger drop in the routine-cognitive share relative to the cheapest locations. This is close to one quarter lower than the average routine-cognitive share of 23 percent in 2015. Furthermore, specification (2) shows that the introduction of MSA controls and industry fixed effects does not affect the impact of local prices on the decline of the routine cognitive share over 1990-2015.

Specification (3) highlights the impact of the 1980 share of routine cognitive workers. Results

[15] The size and the housing price of a city do not follow a 1:1 relationship. The lack of a 1:1 relationship holds empirically, and also in our model in Section 4.2 due to skill-biased technological change and housing supply differences across cities.

Table 3: Change in routine-cognitive share, 1990-2015

	Δrout-cog					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	-0.0427***	-0.0455***			-0.0282**	-0.0281**
	(0.0076)	(0.0113)			(0.0119)	(0.0119)
MSA RC share 1980			-0.2881***		-0.2120***	-0.2003**
			(0.0752)		(0.0748)	(0.0797)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				-0.0275***	-0.0130	-0.0130
				(0.0076)	(0.0087)	(0.0087)
MSA Offshorability 1980						-0.0132
						(0.0268)
Housing supply elasticity		-0.0019	-0.0008	-0.0010	-0.0019	-0.0019
		(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	31.36	10.96	11.41	11.96	10.85	10.47
Adj. R^2	0.122	0.512	0.511	0.508	0.540	0.538
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of routine cognitive occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

show that the impact of the initial share of routine cognitive workers is both statistically and economically significant. A one standard deviation increase in the 1980 share of routine cognitive workers (an increase of 2.9 percentage points in the local share of routine cognitive jobs) is associated with a 0.8 percentage point larger drop subsequently and the effect is statistically significant. Specification (4) shows that a one standard deviation increase in the share of "college-equivalent" workers relative to non-"college-equivalent" workers (representing a 11.1 percentage-point increase in this share) is associated with a 0.9 percentage point larger drop in the routine-cognitive share over 1990-2015. Specification (5) combines all three regressors plus controls in one regression. Both the local price index and the 1980 share of routine cognitive workers continue to be statistically significant, even after accounting for their covariation. However, the partial effect of each is smaller. The effect of a one standard deviation higher house price drops to 0.6 percentage point. Similarly, the effects of a one standard deviation higher 1980 share of routine cognitive workers drops to 0.6 percentage point.

In specification (6) we control for the average degree of offshorability of the jobs in the MSA. Notice that our proxy for the offshorability of jobs in 1980 has a small and not statistically significant effect on the change in the routine cognitive share of MSAs. Nevertheless, our measure of offshorability only highlights the occupation's potential exposure to offshoring, and it is not unlikely that both offshoring and technology adoption have happened concomitantly during the 1990-2015 period. Furthermore, results for the other variables of interest are in line with what we observed in specification (5). The effect of a higher local price index drops to about 60 percent of the observed effect in specification (1), though the difference in the coefficients is minor compared to specification (5). Similarly, the effects of the 1980 share of routine cognitive workers drop by 25 percent. Overall, our results confirm the prediction that expensive locations have seen a substantially larger decline in their share of routine cognitive workers. In Appendix Table A-27 we introduce MSA's employment size in 1980 as a control. As in the case of Appendix Table A-19, MSA size has no statistically significant impact once we control for local real estate prices. Moreover, the impact of house prices on the change in the share of routine.

We have shown that routine cognitive occupations decline faster in expensive cities. This finding is robust to allowing for alternative explanations. When we include variables in the regressions that capture the role of skill-biased technological change, amenities, and home ownership, the estimated relationship between house prices and the decline of routine cognitive jobs is maintained.

We will come back to this finding when we show the impact of IT prices in the estimated model. In Section 4.3, once we have estimated the model, we isolate the effect of the change in IT prices on routine-cognitive employment and derive the same relationship in the model that we document here empirically.

3.2 Patterns of Wage Inequality

So far, our focus has been on the composition of employment by occupation and its differential change across cities. The composition and the change are governed by equilibrium prices. We have already extensively analyzed housing prices, but equilibrium wages play an equally important role in balancing the impact of changes in the relative cost between technology and labor. Next, we analyze the relative wages across cognitive occupations, in particular the evolution across cities with difference house prices.

Wages and House Prices. When wages adjust in response to changes in the price of capital, the ratio of relative wages across regions will typically not be constant. Agents can optimally choose their occupation, and they have idiosyncratic tastes for cities and occupations as well as differences in innate abilities. In order to highlight the need for such potential extensions of the basic mechanism, we briefly present the impact of changes in housing costs and in investment in technology on the relative wages of routine cognitive and non-routine cognitive occupations across cities.

Table 4 shows how the relative MSA-level average wages for routine cognitive and non-routine cognitive occupations change over the period 1990–2015. As we can see, areas that were more expensive in 1980 have seen an increase in the wage premium observed by non-routine cognitive occupations. Specification (1) indicates that places with a local price index one standard deviation

Table 4: Wage ratios NRC-RC: 1990–2015

	$\Delta \ln \left(\frac{W_{NRC}}{W_{RC}} \right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.0559**	0.1497***			0.1268***	0.1258***
	(0.0230)	(0.0393)			(0.0417)	(0.0399)
MSA routine cognitive share 1980			0.6185**		0.4637**	0.2857
			(0.2517)		(0.2314)	(0.2592)
MSA non-routine cognitive share 1980			0.2179		0.0408	-0.0406
			(0.1480)		(0.1947)	(0.1968)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0610**	0.0048	0.0127
				(0.0247)	(0.0319)	(0.0310)
MSA Offshorability 1980						0.1927***
						(0.0691)
Housing supply elasticity		-0.0021	-0.0055*	-0.0057**	-0.0019	-0.0017
		(0.0029)	(0.0028)	(0.0028)	(0.0029)	(0.0026)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	5.94	3.74	3.30	3.55	3.55	4.55
Adj. R^2	0.040	0.212	0.170	0.157	0.222	0.247
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the log ratio of nonroutine cognitive occupation and routine cognitive occupation real average wages between 1990 and 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

higher than the average in 1980 (an increase of 21.4 percent in the local price index) are associated with a 4 percentage point increase in the wage premium of non-routine cognitive occupations relative to routine cognitive occupations over 1990-2015. Moreover, results are qualitatively and quantitatively robust to including the previously discussed controls, such as the relative share of "college-equivalent" workers, the share of offshorable jobs in the MSA, and the share of routine cognitive and non-routine cognitive jobs in the MSA in 1980.

In particular, specification (5) shows that places with a local price index one standard deviation higher than the average in 1980 (an increase of 21.4 percent in the local price index) are associated with about a 3.5 percentage point larger increase in the wage premium of non-routine cognitive occupations relative to routine cognitive occupations over 1990-2015.

4 The Economic Mechanism

In order to highlight the economic mechanism and the general equilibrium effects of technological change on polarization, we present a model where firms located in heterogeneous cities hire heterogeneously skilled workers. Simultaneously, firms adopt IT technology. The objective is to analyze the equilibrium allocation of workers of different skills to cities and in different occupations (routine and non-routine) in the light of changing prices of IT technology. First, in Section 4.1 we propose a simplified model that we can solve analytically in order to convey the basic mechanism and results. Then, in Section 4.2 we extend the model to make it suitable for the quantitative exercise. In Section 4.3, we estimate the general quantitative model.

4.1 The Basic Model and Analytical Results

Equilibrium housing prices are a key driver behind polarization and inequality in our mechanism. We therefore lay out a framework with worker mobility and competitive labor and housing markets. In response to changes in the technology, prices and wages adjust and workers choose to relocate. The equilibrium across space thus reflects the joint effect of technology and housing prices on wages. A feature that distinguishes our model from most of the literature with two types is that we have rich heterogeneity in worker skills and occupations. This heterogeneity allows us to capture realistic difference across the distribution and generate real polarization. In the basic model workers' skill and occupation are interchangeable, because each worker type is assigned to a fixed job type.

Cities and Population. Consider an economy with heterogeneously skilled workers. Workers are indexed by a skill type i. For now, let the types be discrete: $i \in \mathcal{I} = \{1, ..., I\}$. Associated with this skill order is a level of productivity x_i. Denote the country-wide measure of skills of type i by M_i. Let there be J locations (cities) $j \in \mathcal{J} = \{1, ..., J\}$. The amount of land in a city is fixed and denoted by H_j. Land is a scarce resource.

Preferences. Citizens of skill type i who live in city j have preferences over consumption c_{ij}, and the amount of land (or housing) h_{ij}. The consumption good is a tradable numeraire good with price equal to one. The price per unit of land is denoted by p_j. We think of the expenditure on housing as the flow value that compensates for the depreciation, interest on capital, etc. In a competitive rental market, the flow payment will equal the rental price.[16] A worker has consumer preferences over the quantities of goods and housing c and h that are represented by: $u(c, h) = c^{1-\alpha}h^{\alpha}$, where $\alpha \in [0, 1]$. Workers are perfectly mobile, so they can relocate instantaneously and at no cost to another city. Because workers with the same skill are identical, in equilibrium each of them should obtain the same utility level wherever they choose to locate. Therefore for any two cities j, j' it must be the case that the respective consumption bundles satisfy $u(c_{ij}, h_{ij}) = u(c_{ij'}, h_{ij'})$, for all skill types $\forall i \in \{1, ..., I\}$.

Technology. Cities differ in their total factor productivity (TFP) which is denoted by A_j. For now, we assume that TFP is exogenous. We think of it as representing a city's productive amenities, infrastructure, historical industries, persistence of investments, etc.

[16]We abstract from the housing production technology; for example, we assume that the entire housing stock is held by a zero measure of absentee landlords.

In each city, there is a technology operated by a representative firm that has access to a city-specific TFP A_j. Output is produced by choosing the right mix of differently skilled workers i as well as the amount of capital k. While labor markets are local and workers must live in the city in which they are employed, capital markets are global and even large cities are small open economies in the capital markets. We also consider that firms rent capital that is owned by a zero measure of absentee capitalists. For each skill i, a firm in city j chooses a level of employment m_{ij} and produces output: $A_j F(m_{1j}, ..., m_{Ij}, k_j)$, where

$$A_j F(m_{1j}, m_{2j}, m_{3j}, k) = A_j \left\{ m_{1j}^{\lambda_1} A_{l,1} + \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k \right)^{\frac{\lambda_2}{\gamma}} + m_{3j}^{\lambda_3} A_{l,3} \right\}, \text{ where } \quad \lambda_2 < \gamma. \quad (1)$$

We have chosen the particular functional form of the production function for simplicity, following Eeckhout et al. (2014), while allowing for substitution between capital and labor as in Krusell et al. (2000). We assume additive separability which enables us to derive analytical results. This is the simplest production function that allows for gross substitutability between middle "skill" occupation workers and capital, thus capturing automation-driven job polarization, which requires a minimum of three occupations in order to capture job polarization. Krusell et al. (2000) focuses on the gross complementarity between high skill workers and capital (hence skill-biased technological change), and their focus on two skill types does not let them capture polarization.[17]

Firms pay wages w_{ij} for workers of type i. It is important to note that wages depend on the city j because citizens freely locate between cities not based on the highest wage, but, given housing price differences, based on the highest utility. Like land and capital, firms are owned by absentee capitalists (or equivalently, all citizens own an equal share in the mutual fund that owns all the land and all the firms). Finally, we consider that the rental price for capital is given by $r > 0$ which is determined in the global market and taken as given by firms in the different cities.

Market Clearing. In the country-wide market for skilled labor, markets for skills clear market by market, and for housing, there is market clearing within each city:

$$\sum_{j=1}^{J} m_{ij} = M_i, \ \forall i \qquad \sum_{i=1}^{I} h_{ij} m_{ij} = H_j, \ \forall j. \quad (2)$$

The Citizen's Problem. Within a given city j and given a wage schedule w_{ij}, a citizen chooses consumption bundles $\{c_{ij}, h_{ij}\}$ to maximize utility subject to the budget constraint (where the

[17] In previous versions, we separately discussed different nestings of capital, that captured skill-biased technological change, and showed its implications for the sorting of workers (see Eeckhout, Hedtrich, and Pinheiro (2021)). The earlier results also show that nesting different types of labor with capital is generally not isomorphic.

tradable consumption good is the numeraire, i.e. with price unity)

$$\begin{aligned} \max_{\{c_{ij},h_{ij}\}} u(c_{ij},h_{ij}) &= c_{ij}^{1-\alpha}h_{ij}^{\alpha} \\ \text{s.t. } c_{ij}+p_jh_{ij} &\leq w_{ij} \end{aligned} \tag{3}$$

for all i, j. Maximizing the utility, we obtain $c_{ij}^{\star} = (1-\alpha)w_{ij}$ and $h_{ij}^{\star} = \alpha\frac{w_{ij}}{p_j}$.

The Firm's Problem. All firms are price-takers and do not affect wages. Wages are determined simultaneously in each submarket i, j while capital rent is determined in the global market. Given the city production technology, a firm's problem is given by:

$$\max_{m_{ij},\forall i} A_jF(m_{1j},...,m_{Ij},k_j) - \sum_{i=1}^{I} w_{ij}m_{ij} - rk_j, \tag{4}$$

subject to the constraint that $m_{ij} \geq 0$ and $k \geq 0$. The first-order conditions are: $A_jF_{m_{ij}}(m_{ij},k_j) = w_{ij}, \forall i$ and $A_jF_{k_j}(m_{ij},k_j) = r$.

A spatial equilibrium is defined as a set of wages, housing prices, a distribution of workers across space, and capital that satisfy the first-order conditions and market clearing. We now turn to the main analytical results.

Main Theoretical Results. Given these simplifications, we first establish the relationship between TFP and house prices. When cities have the same amount of land, we can establish the following result.

Proposition 1 (TFP and Housing Prices) *The more productive city has higher housing prices:* $A_i > A_j \Rightarrow p_i > p_j$.

Consequently, the city with the highest TFP is also the one with the highest housing prices. We establish this result for cities with an identical supply of land. Clearly, the supply of land is important in our model, since in a city with an extremely small geographical area, labor demand would drive up housing prices, all else equal. This may therefore make it more expensive to live in such a city even if the productivity is lower. Because in our empirical application we consider large metropolitan areas (New York City MSA for example includes large parts of New Jersey and Connecticut), we believe that this assumption does not lead to much loss of generality.[18]

We now focus on the relation between demand for capital and TFP. As proposition 2 shows, the city with higher TFP also demands more capital. The intuition is straightforward. In cities with higher TFP, housing prices are higher and workers must be compensated in order to afford

[18]In fact, the equal supply of housing condition is only sufficient for the proof, but not necessary. However, our model does not address the important issue of within-city geographical heterogeneity, as analyzed, for example, in Lucas and Rossi-Hansberg (2002). In our application, all heterogeneity is absorbed in the pricing index by means of the hedonic regression.

living in a more expensive place. Furthermore, since firms with higher TFP hire more of all skill levels, the decreasing marginal returns are also stronger, leading to an increase in the use of capital in order to replace skilled workers. Hence, high-TFP cities demand more capital.

Proposition 2 (TFP and Capital Demand) *The more productive city has higher investment in IT:* $A_i > A_j \Rightarrow k_i > k_j$.

Then, in theorem 1 we show that the city with the high TFP is also larger. In fact, we are able to show that, in equilibrium, the high-TFP city has more workers at all skill levels.

Theorem 1 (IT and City Size) *The more productive city has a larger population:* $A_1 > A_2 \Rightarrow S_1 > S_2$.

Theorem 1 establishes a relationship that is consistent with the positive correlation between size and house prices that we observe in the data. This empirical relationship is robust across different economies, and the theorem establishes that the model is in line with this robust relationship.

Moreover, theorem 2 shows that, in the case in which $\lambda_i \equiv \lambda$ for all skills, a high-TFP city has proportionately more of both high and low skill workers than low-TFP cities. This is true even though high-TFP cities have more workers of all types in absolute numbers. Consequently, the high-TFP city is more unequal in terms of its skill distribution.

Theorem 2 (IT and Spatial Sorting) *Assume* $\lambda_i \equiv \lambda$ *for* $i \in \{1, 2, 3\}$. *Then the larger city has a more unequal skill distribution:* $A_1 > A_2$ *implies that city 1 has a thicker tailed skill distribution.*

We can also show that high-TFP cities will have proportionately more capital per worker.

Corollary 1 *The larger city has more capital per capita:* $A_1 > A_2$ *implies that* $\frac{k_1}{S_1} > \frac{k_2}{S_2}$.

Theorem 2 (and Corollary 1) establishes a relationship between the variance of the skill distribution and city size, and shows that the finding in Eeckhout et al. (2014) can be obtained through capital-labor substitution of mid-skill workers. This qualitatively replicates the empirical findings. In the data we find that expensive cities (in terms of house prices) use IT more intensively and have a larger decline in the share of routine-cognitive workers. This is consistent with a comparison of the allocation in Theorem 2 and the allocation absent capital.

Finally, let's define the middle composite $X_j = \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k\right)^{\frac{1}{\gamma}}$. Then defining $\sigma_{i,l}$ the elasticity of substitution between occupations i and l, and $\sigma_{i,X}$ the elasticity of substitution between occupation i and middle composite X. Then, based on equation (1), we obtain the following lemma:

Lemma 1 *Assume* $\lambda_i \equiv \lambda$ *for* $i \in \{1, 2, 3\}$. *The elasticities of substitution between low or high skilled labor and the middle composite are* $\sigma_{1,3} = \sigma_{1,X} = \sigma_{3,X} = \frac{1}{1-\lambda}$, *while the elasticity of substitution between the middle occupation and ICT capital* $\sigma_{2,k} = \frac{1}{1-\gamma}$.

The result presented in lemma 1, while straightforward, helps us to connect the technology from the basic model to the more general model that we use in our empirical section. In particular, in the case $\lambda_i \equiv \lambda$ for $i \in \{1, 2, 3\}$, the elasticity of substitution across CES composites in the general production function presented below in equation (6) is the same as the one obtained for equation (1).

4.2 General Model

For the general model that we quantify, we extend the basic model to include some realistic features: multidimensional skills in a Roy-like setup; tastes for amenities of jobs and locations; a more general production technology; and a varying housing supply. In the general model, workers' skills and occupation are not interchangeable anymore. Each worker has occupation-specific skills and chooses the occupation in equilibrium.

Skills and Amenities. Workers are heterogeneous in their skills $\mathbf{s}$, tastes for jobs $\mathbf{t}$, and tastes for locations $\mathbf{a}$. Each worker is endowed with a set of skills for each occupation i, summarized by the vector $\mathbf{s} = [s_1, \ldots, s_I]$. The skill vector represents how many efficiency units of labor a worker could supply in each occupation. The distribution of skills is given by $G(\mathbf{s})$. The income a worker earns in an occupation is the product of efficiency units and the wage per efficiency unit: $w_{i,j}(\mathbf{s}) = s_i \tilde{w}_{i,j}$.

A worker's utility from choosing a location and occupation depends not only on real income but also on the idiosyncratic taste for occupations and locations. The indirect utility V of a location-occupation pair for a worker with skills $\mathbf{s}$ and tastes $\mathbf{a}, \mathbf{t}$ is

$$V(i, j, \mathbf{s}, \mathbf{a}, \mathbf{t}) = a_j t_i v(\tilde{w}_{i,j} s_i, p_j). \tag{5}$$

The idiosyncratic taste for location a_j follows a Fréchet distribution with shape parameter τ and location parameter $\bar{a}_j$. The idiosyncratic taste for occupation t_i follows a Fréchet distribution with shape parameter η and location parameter $\bar{t}_i$. Idiosyncratic tastes are i.i.d. across individuals and locations. For simplicity we assume that the taste for a location is drawn first and after a worker has chosen a location, her taste for occupations is drawn followed by the occupation choice. This setup represents the idea that the location choice is relatively more permanent compared to the occupation choice. Given the specification of tastes we can derive the probability distribution of workers' occupation and location choices conditional on skills and prices in closed form.

Technology. In each city, there is a technology operated by a representative firm with access to the city-specific technology. The production function F has a nested CES structure

$$A_j F(\mathbf{m}_j, \mathbf{k}_j, \mathbf{A}_j) = A_j \left\{ \sum_i A_{l,ij}^{\frac{\lambda}{\gamma_i}} \left[m_{ij}^{\gamma_i} + A_{k,i} k_{ij}^{\gamma_i} \right]^{\frac{\lambda}{\gamma_i}} \right\}^{\frac{1}{\lambda}}. \tag{6}$$

A_j is the total factor productivity of city j. Production combines labor and capital (IT) within occupations with a finite elasticity of substitution, which is governed by γ_i.[19] The elasticity of substitution between capital and labor is occupation specific, allowing capital to complement labor in some occupations and substitute labor in others. Occupation-enhancing productivity $A_{l,ij}$ for each occupation i is allowed to vary across cities j, to capture preexisting specialization of cities. The capital productivity, relative to labor, $A_{k,i}$ is the same across cities, implying that two cities with the same relative price of capital and labor would employ capital and labor in the same ratio in an occupation. In other words, we assume that the capital technology used in a given occupation has no inherent bias towards specific cities.

The output of the different occupations is aggregated with a finite elasticity of substitution $\frac{1}{1-\lambda}$. The final output is freely traded and its price is normalized to 1. Firms maximize profits and are price takers. Both output and factor markets are competitive; thus, both labor and capital are paid according to their marginal product. Each efficiency unit of labor costs $\tilde{w}_{i,j}$ and capital supply is fully elastic at the rental rate r, which is taken as given.

Housing. The housing market is competitive and the housing stock is owned by absentee landlords.[20] Housing supply follows the price-quantity schedule

$$p_j(H) = \phi_j H^{\epsilon_{p,j}}. \tag{7}$$

In equilibrium, housing supply H adjusts such that the housing amount demanded by workers equals the amount supplied. The inverse housing supply elasticity ϵ_p is finite and captures limitations to increasing the stock of housing in a given city. Furthermore, we allow the housing supply elasticity to vary across cities. The revenue from the housing market is consumed by absentee landowners. Housing demand in a city is given by

$$H_j^D = \frac{\alpha}{p_j} \int s_i \tilde{w}_{i,j} P(occ = i, city = j | skill = \mathbf{s}) dG(\mathbf{s}). \tag{8}$$

The Worker's Solution. Within a given city j and given a wage $w_{ij} = \tilde{w}_{ij} s_i$, a citizen has the same utility as in the basic model. Substituting the equilibrium values in the utility function, we can write $v(w_{ij}, p_j) = (1-\alpha)^{(1-\alpha)} \alpha^\alpha \frac{w_{ij}}{p_j^\alpha}$, which completes the derivation of the indirect utility of a location-occupation pair in equation (5).

Given the specification of tastes, we can derive the probability distribution of workers' occupation

[19] The within-occupation elasticity of substitution between capital and labor is $\frac{1}{1-\gamma_i}$

[20] If landlords were treated as residents, then how it affects the equilibrium allocation depends on the way rents are distributed. For example, if residents own a representative portfolio of the housing stock, then there is an income effect (all residents receive and equal increase in their income) but there is no distributional effect. This would not change the allocation of skills. Instead, if households own the house they live in, there would be distributional implications. Those are interesting but we consider they are beyond the scope of the current paper and leave them for future work.

and location choices conditional on skills and prices in closed form.

$$\bar{u}(i,j,\mathbf{s}) = \bar{a}_j \bar{t}_i v(s_i \tilde{w}_{ij}, p_j) \tag{9}$$

$$\mathbb{E}_{\mathbf{t}}[\max_i u(i,j,\mathbf{s})] = \sum_i \bar{u}(i,j,\mathbf{s}) \left(\frac{1}{\sum_{i'} \left(\frac{\bar{u}(i,j,\mathbf{s})}{\bar{u}(i',j,\mathbf{s})} \right)^{-\eta}} \right)^{1-\frac{1}{\eta}} \Gamma\left(1 - \frac{1}{\eta}\right) \tag{10}$$

$$P(\text{city} = j|\text{skill} = \mathbf{s}) = \frac{\mathbb{E}_{\mathbf{t}}[\max_i u(i,j,\mathbf{s})]^\tau}{\sum_{j'=1}^J \mathbb{E}_{\mathbf{t}}[\max_i u(i,j',\mathbf{s})]^\tau} \tag{11}$$

$$P(\text{occ} = i|\text{city} = j, \text{skill} = \mathbf{s}) = \frac{u(i,j,\mathbf{s})^\eta}{\sum_{i'=1}^I u(i',j,\mathbf{s})^\eta} \tag{12}$$

See Appendix G for the derivation. The joint distribution of skills and choices of occupation and location then follows as

$$P(\text{skill} = \mathbf{s}, \text{occ} = i, \text{city} = j) = G(\mathbf{s}) P(\text{city} = j|\text{skill} = \mathbf{s}) P(\text{occ} = i|\text{city} = j, \text{skill} = \mathbf{s}). \tag{13}$$

The Firm's Solution. All firms are price takers and do not affect wages or capital markets. Wages are determined simultaneously in each submarket (i,j), while capital rent is determined in the global market. Given the city production technology, a firm's problem is given by:

$$\max_{m_{ij}, \forall i} A_j F(m_{1j}, ..., m_{Ij}, k_j) - \sum_{i=1}^I w_{ij} m_{ij} - r k_j, \tag{14}$$

subject to the constraint that $m_{ij} \geq 0$ and $k \geq 0$. The first-order conditions are: $A_j F_{m_{ij}}(m_{ij}, k_j) = w_{ij}, \forall i$ and $A_j F_{k_j}(m_{ij}, k_j) = r$.[21]

For the general model setup with the CES technology, optimal labor and capital demand obtained from profit maximization satisfies

$$\tilde{w}_{i,j} = A_j \left\{ \sum_i A_{l,ij}^{\frac{\gamma_i}{\lambda}} \left[m_{ij}^{\gamma_i} + A_{k,i} k_{ij}^{\gamma_i} \right]^{\frac{\lambda}{\gamma_i}} \right\}^{\frac{1}{\lambda}-1} A_{l,ij}^{\frac{\gamma_i}{\lambda}} \left[m_{ij}^{\gamma_i} + A_{k,i} k_{ij}^{\gamma_i} \right]^{\frac{\lambda}{\gamma_i}-1} m_{ij}^{\gamma_i - 1} \tag{15}$$

$$r = A_j \left\{ \sum_i A_{l,ij}^{\frac{\gamma_i}{\lambda}} \left[m_{ij}^{\gamma_i} + A_{k,i} k_{ij}^{\gamma_i} \right]^{\frac{\lambda}{\gamma_i}} \right\}^{\frac{1}{\lambda}-1} A_{l,ij}^{\frac{\gamma_i}{\lambda}} \left[m_{ij}^{\gamma_i} + A_{k,i} k_{ij}^{\gamma_i} \right]^{\frac{\lambda}{\gamma_i}-1} A_{k,i} k_{ij}^{\gamma_i - 1}. \tag{16}$$

Even without fully solving the system of equations for the equilibrium wages, observation of the first-order condition reveals that productivity between different skills i in a given city is governed by three components: (1) the productivity $A_{l,i}$ of the skilled labor and how fast it increases in i; (2) the measure of skills m_{ij} employed (wages decrease in the measure employed from the concavity of the technology); and (3) the degree of concavity γ_i, indicating how fast congestion builds up in a

[21] In what follows, the non-negativity constraint on m_{ij} and k_j are dropped. This is justified whenever the technology satisfies the Inada condition that marginal product at zero tends to infinity whenever A_j is positive. This will be the case since we focus on variations of the CES technology.

particular skill. Without loss of generality, we assume that wages are monotonic in the order i.[22]

4.3 Estimation

In this section we quantify the economic mechanism using our model. Our model is set up to capture key features of the data. The main point for the analysis of the impact of IT on the labor market is to give a central role to housing prices. Through changing prices for IT investment, worker mobility determines equilibrium wages and housing prices. The differential effect on differently skilled workers comes from the technology. We allow for potentially heterogeneous effects based on the type of job or workers' skills (Autor and Dorn, 2013; Krusell et al., 2000). We do this by making the elasticity of substitution between labor and IT occupation specific. To model workers' responses in terms of labor supply across jobs, we model the occupation choice in the spirit of Roy (1951) and allow for idiosyncratic tastes for occupations. To capture a more realistic supply elasticity of workers across cities, we model idiosyncratic tastes for cities, where workers trade off local wages, housing costs, and their valuation of local amenities when they choose where to live. Finally, following the evidence in Saiz (2010), the housing market is modeled as having a finite supply elasticity that varies across cities to capture differences in housing supply restrictions.

There are of course alternative explanations and mechanisms that can account for the same observed patterns in the data. The most prominent alternative is the role of agglomeration externalities (Baum-Snow et al., 2018; Rossi-Hansberg et al., 2019; Diamond, 2016). One of the advantages of our approach is that it allows us to isolate the role of IT prices from agglomeration externalities. We discuss this in further detail below.

Estimation Approach. We estimate the main model parameters by indirect inference (Gourieroux et al., 1993), after we calibrate some parameters based on external evidence. In particular, we estimate a vector of model parameters ω by minimizing the weighted square distance between a vector of moments estimated in the data $\widehat{m}$ and the corresponding model-implied moments $m(\omega)$. The model moments are directly calculated from the equilibrium distribution of workers and prices.

To capture heterogeneity across cities in the data, we bin them into 18 distinct groups based on their rent index calculated from the 1980 census. Each bin approximately represents an equal amount of workers. We bin cities into groups, in order to lower the dimensionality of the model, while still representing the important cross-sectional variation in terms of housing costs, employment and wages in the data. Occupations are grouped as described in Section 2, details of the occupation classification and additional descriptive statistics are reported in Appendix A.1. See Appendix G for details on the estimation procedure and the calculation of moments.

[22]For a given order i, wages may not be monotonic as they depend on the relative supply of skills as well as on $A_{l,i}$. If they are not, we can relabel skills such that the order i corresponds to the order of wages. Alternatively, we can allow for the possibility that higher-skill workers can perform lower-skill jobs. Workers will drop job type until wages are non-decreasing. Then the distribution of workers is endogenous, and given this endogenous distribution, all our results go through. For clarity of the exposition, we will assume that the distribution of skills ensures that wages are monotonic.

The following are the externally calibrated parameters. Following Kennan and Walker (2011) and Monte et al. (2018), we set the scale parameter of the Fréchet distributions of location tastes within their range of estimates to $\tau = 4$. The scale parameter of the taste for occupations is set to $\eta = 5$ following evidence by Berger et al. (2019).[23] Further, we set the elasticity of substitution of output across occupation nests at $\frac{3}{4}$, implying a value of $\lambda = -0.33$. We pick this value to fall within the range of estimates by Goos et al. (2014), who estimate an elasticity of substitution of 0.9 between tasks of differing routine intensity, and Lee and Shin (2017), who estimate an elasticity of substitution of 0.7 between different tasks and an elasticity of substitution of 0.34 between managers and other workers. Further, we calibrate the housing supply price-quantity elasticity ϵ_j directly to the values estimated by Saiz (2010). In Appendix G.6 we show that the results are not sensitive to the exact choice of values for the external parameters.

We target the following moments to estimate parameters:

1. the average wage in each city to estimate the average productivity by city A_j (1 moment and 1 parameter per city),

2. the rent index in each city to estimate the intercept of the housing supply function ϕ_j (1 moment and 1 parameter per city),

3. the relative size of cities to estimate the parameter governing the average taste for a city $\bar{a}_j$, with the normalization $\bar{a}_1 = 1$ (1 moment and 1 parameter per city, except city 1),

4. the share of workers employed in each occupation group in the whole economy, and the difference in said employment shares across cities. The employment shares are used to inform the relative productivity across occupations and cities. This corresponds to the parameter $A_{l,ij}$ with the normalization that $A_{l,RCj} = 1 \, \forall j$ (3 moments and 3 parameters per city),

5. the average log wage (per week in full-time jobs) by occupation to inform the average taste for occupations $\bar{t}_i$, with the normalization $\bar{t}_1 = 1$ (3 moments and 3 parameters),

6. the standard deviation of log wages by occupation to inform the standard deviations σ_i of the log-normal skill distribution (4 moments and 4 parameters),

7. the relative importance of PCs across occupations calculated from O*NET as a measure of relative IT usage per worker across occupations, combined with the aggregate IT share out of labor and IT spending as calculated in Eden and Gaggl (2018) to estimate the productivity of capital relative to labor $A_{k,i}$ by occupation group (4 moments and 4 parameters),

8. the elasticity of employment shares with respect to IT prices as implied by the calibrated model in vom Lehn (2020) to target the elasticity of substitution between capital and labor by occupation group. This target also implies that aggregate effects of IT will be very similar

[23] Their estimate is 5.38 for "within market" substitutability of firms.

to those in their analysis. We do not directly estimate the elasticity of substitution from the cross-section of cities, because the data does not allow us to measure IT usage by occupation. Following the classification in vom Lehn (2020), we set γ to be equal for routine cognitive and routine manual jobs, but keep them as distinct job categories in our model. (3 moments and 3 parameters).

The overall fit is very good. We show aggregate moments and corresponding parameters in Table 5 and Table 6. The city-level moments and parameters are shown in Appendix G.5. For an overview of employment by occupation see also Figure A-1.

Table 5: Moments 2015 and Model fit

Panel A: Occupation-level Moments

	non-routine manual		routine manual		routine cognitive		non-routine cognitive	
Moment	**Data**	**Model**	**Data**	**Model**	**Data**	**Model**	**Data**	**Model**
Share in %	12.0	13.0	22.0	22.0	24.0	23.0	43.0	43.0
	(0.26)		(0.58)		(0.27)		(0.74)	
$log(w)$	6.2	6.2	6.6	6.6	6.7	6.7	7.2	7.2
	(0.013)		(0.012)		(0.018)		(0.024)	
$\sigma(log(w))$	0.55	0.54	0.59	0.59	0.68	0.69	0.7	0.7
	(0.0039)		(0.0051)		(0.0086)		(0.0052)	
Relative PC importance	0.16	0.16	0.17	0.17	0.32	0.33	0.34	0.34

Panel B: Additional External Moments

Moment	**Data**	**Model**
ICT Share	0.1	0.11
ICT price index, Base 2015 = 1	1.0	1.0
Elasticity NRM share - IT price	-0.052	-0.051
Elasticity R share - IT price	0.11	0.11
Elasticity NRC share - IT price	-0.11	-0.11

Note: Data moments calculated from the American Community Survey 2014-2016 (Ruggles et al., 2020) and O*NET. Standard errors in parentheses calculated by bootstrap resampling of MSAs. Cities are grouped based on the 1980 rent index calculated for each MSA, so that each group represents approximately the same share of the population. IT share calculated as in Eden and Gaggl (2018) and elasticity of employment with respect to IT price calculated from vom Lehn (2020). See Appendix G for details.

In Panel A of Table 5, we present moments calculated at the occupation level. Average wages vary substantially across occupation groups. Wages in non-routine cognitive jobs are more than twice as large as in non-routine manual jobs. Wage inequality is, however, not only substantial between occupations but also within. Within-occupation group log wage standard deviations range from 0.55 in non-routine manual jobs to 0.7 in non-routine cognitive jobs. The importance of PC usage, as measured in O*NET, is larger in cognitive jobs compared to manual jobs. As the scale of the measure is not in units of the final good, we use it only to compare across occupations. We normalize such that the measure sums to one. To measure the overall importance of IT in the economy, we calculate the share of aggregate costs of IT out of labor and IT (Eden and Gaggl, 2018).

The remaining targets are the elasticities of occupation employment shares with respect to IT prices based on the estimation of vom Lehn (2020). We use the calibration for the 1990s. We target an elasticity that is negative for non-routine cognitive jobs, and positive for routine jobs. This pattern is in line with IT substituting labor in routine jobs, while complementing labor in non-routine cognitive jobs. Finally, the implied elasticity of the non-routine manual share is negative but smaller in magnitude.

Table 6: Estimated Parameters 2015

Panel A: Occupation level Parameters

Parameter	non-routine manual	routine manual	routine cognitive	non-routine cognitive
Occupation Amenity $\bar{t}_i$	1.0	0.43	0.6	0.27
		(0.1)	(0.15)	(0.062)
Std dev. Skills $\sigma_i(log(s))$	2.1	1.0	1.5	0.93
	(0.5)	(0.033)	(0.058)	(0.0086)
Capital Productivity $\frac{A_{k,i}}{A_{l,i}}$	0.12	0.013	0.024	0.21
Capital-Labor substitution parameter γ_i	0.2	0.6	0.6	-0.15

Panel B: Additional Parameters

Parameter	**Value**	**Source/Explanation**
τ	4.0	Dispersion of tastes for locations (Kennan and Walker, 2011; Monte et al., 2018)
η	5.0	Dispersion of tastes for jobs (Berger et al., 2019)
λ	-0.33	Occupation output elasticity $\frac{3}{4}$ (Goos et al., 2014; Lee and Shin, 2017)

Note: Standard errors in parentheses. See Appendix G for details.

We report the estimated parameters of the model in Table 6. For the elasticity of substitution (EoS) between capital and labor by occupation we find: 1.25 in non-routine manual jobs, 2.5 in routine jobs and 0.87 in non-routine cognitive jobs (see the value of γ_i in Table 6, which translates into the $\text{EoS}_i = \frac{1}{1-\gamma_i}$). Thus, IT is estimated to be complementary to labor in non-routine cognitive occupations, while it substitutes labor in routine cognitive and manual jobs. This suggests that IT impacts the labor market through both substituting away labor in routine cognitive and manual jobs and by complementing labor in non-routine cognitive jobs. We discuss the quantitative implications of our estimates for the allocation of labor to jobs and cities in the next section. The closest comparable estimates of such substitution elasticities are provided by Caunedo et al. (2023). They find an estimate of the elasticity of substitution between labor and "capital embodied technological change" just below one for professionals and managers, a large part of the occupations we classify as non-routine cognitive jobs. For administrative services, classified in this paper as routine cognitive, they estimate an elasticity of 2.18. For low skill services, corresponding to the non-routine manual category in this paper, they estimate an elasticity of 1.32. Thus, their estimates are almost identical to our calibration and suggest that other technologies may feature similar bias as IT, which would only strengthen our results. Similarly, Adachi (2021) estimates an elasticity of substitution between robots and labor that range between 0.8 and 4 depending on the occupation group, thus also suggesting a large variation in the substitutability between robots and labor by type of job.

The remaining parameters in Panel A are the workers' average taste for occupations and the standard deviation of skills in each type of job. The parameter governing the location of the Fréchet distribution of tastes for jobs varies inversely with an occupation's average wage, since the model features a competitive labor market; wages would otherwise (almost) equalize.[24] The standard deviation of skills is estimated to fit the standard deviation of wages *within* occupations, given the normalization that the mean of the log skill distribution is zero in each dimension. This leads to large estimated standard deviations of skills for occupations with a smaller employment share, e.g. non-routine manual jobs. The within-occupation variability in skills replicates not only the within-occupation variability of wages, but it also captures to what extent workers' skills determine their occupation choice.

Finally, the city level parameters governing the local importance of each occupation, overall productivity and housing supply are shown in Appendix G.5.

The Rise of IT in the Estimated Model. We consider an experiment where the quality-adjusted price of IT capital falls from its 1990 level to its value in 2015, which is by approximately 65 percent. We take the model as estimated for 2015 to be the baseline and compare it to the model-implied allocation when only IT prices change back to their 1990 level. With this exercise, we evaluate to what extent the fall in prices of IT can explain employment and wage trends in the US between 1990 and 2015. We show results not only for the economy, but focus on the heterogeneous impact across low- and high-rent cities.

Note that the results in Table 7 roll back the price of IT to 1990 levels and allow the model to tell us what the counterfactual allocation of employment and wages would be across locations in that world, as compared to the data. Figure 4 then links this directly to the empirical results from Section 3.

Table 7 shows the changes in employment shares and wages across occupations in the economy. The first column shows the change in the data between 1990 and 2015 and the second column shows the difference between the model allocation with 1990 IT prices and the 2015 allocation. We find that the fall in IT prices explains about 20 percent of the fall in the routine-cognitive employment share and the rise in the non-routine cognitive employment share. The overall predicted changes for manual jobs are much smaller. These results reflect that IT is more intensively used in jobs that involve more cognitive tasks, and the relatively high substitutability of IT and routine cognitive labor in comparison to non-routine cognitive labor. The responses of wages are generally positive in the model, as the fall in IT prices raises overall productivity. However, again the wages reflect the relative rise in demand for non-routine cognitive labor compared to routine cognitive labor

[24] There is a finite supply elasticity of labor, so wages would not equalize exactly.

Table 7: The rise of IT: Employment and Wages

	Δ Data 1990-2015	**Δ Model IT price ↓ 65%**
Employment Share by Occupation in pp		
non-routine manual	3.3	0.013
routine manual	-7.8	-0.42
routine cognitive	-5.9	-1.3
non-routine cognitive	10.0	1.7
Avg log wage by Occupation		
non-routine manual	-0.03	0.1
routine manual	-0.068	0.097
routine cognitive	0.049	0.074
non-routine cognitive	0.15	0.12

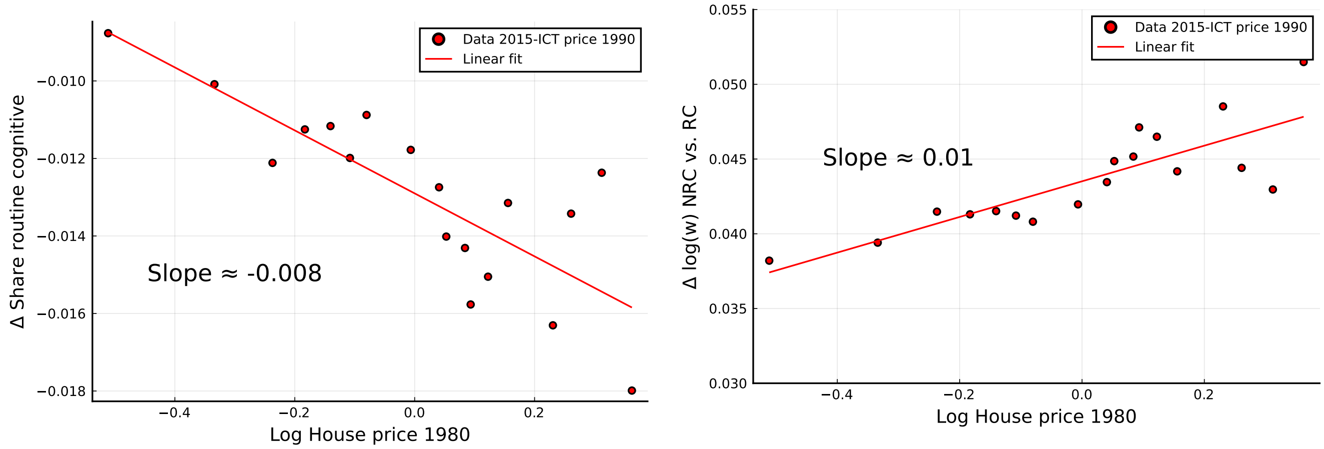
Note: The column Δ Model is calculated as the difference between the model allocation at the estimated parameters in Table 6 with IT prices normalized to $r = 1$, and the model allocation at $\hat{r} = \frac{r_{1990}}{r_{2015}}$ with all other parameters held constant. Here r_y denotes the price of IT relative to the GDP deflator in year y, calculated as in Eden and Gaggl (2018).

with the wage gap rising by 4.5 log points in response to the fall in IT prices, which is almost half the change in the data between 1990 and 2015. At this point it is important to note that the counterfactual holds the production technology constant. vom Lehn (2020) discusses in more detail to what extent in such an environment the fall in IT prices can explain the changes in employment across occupations at the aggregate level.

We now turn to the main goal of the exercise. To what extent can the adoption of IT explain the more intensive replacement of routine cognitive employment in initially expensive cities, and to what extent can it explain the larger rise in the wage premium of non-routine cognitive over routine cognitive workers? The results are shown in Figure 4. Panel 4a shows that the fall in routine cognitive employment has been much more pronounced in cities with initially high house prices. The fall in the most expensive locations is about twice as large as in the cheapest locations. The semi-elasticity of the change in the employment share of routine cognitive jobs with respect to house prices in 1980 is $-.008$. In Figure 3 we plot the corresponding change in the data between 1990 and 2015 and in Table 3 we show the corresponding point estimates for different specifications. The point estimate shown in column 6 is -0.028. Thus, the fall in IT prices can by itself explain 30 percent ($\frac{-0.008}{-0.028} \approx 30\%$) of the sorting of routine cognitive work away from expensive cities.[25] Thus, the model simulation implies that the fall in IT prices had an important effect on the allocation of jobs across space. In terms of the wage premium of non-routine cognitive work over routine cognitive work, we find a larger increase in expensive cities in the model. The corresponding estimates for the change in the data between 1990 and 2015 are shown in Table 4. The model implies an elasticity of the rise in the wage premium with respect to house prices in 1980 of 0.01,

[25] Observe that the 30% number refers to the elasticity of the decline in the routine-cognitive share with respect to local house prices in the initial allocation and thus summarizes the role of prices throughout the *entire* distribution. Figure 4 shows a stable log-linear relationship, and therefore the 30% effect captures well the differential impact IT has on polarization in cities across the entire distribution.

while the estimate for 1990-2015 is 0.126. Thus, the wage premium of non-routine cognitive work has risen substantially faster in the data than what is implied by the fall in IT prices.

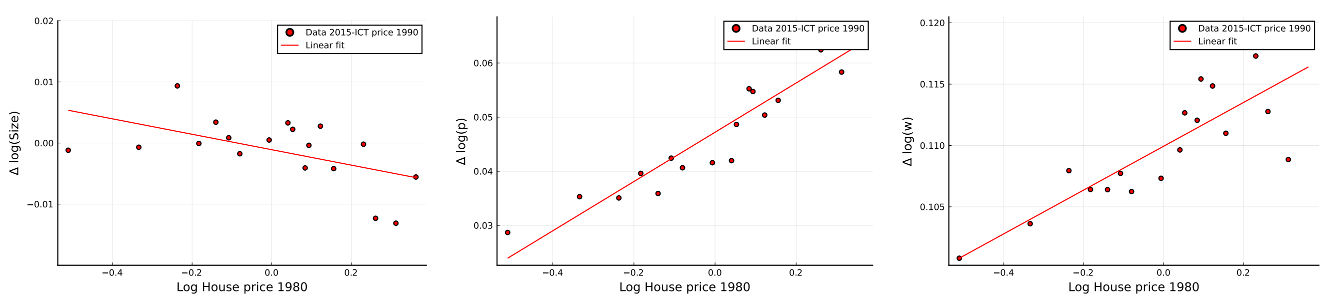


(a) Routine-cognitive share

(b) Wage premium: non-routine over routine cognitive

Figure 4: IT and Urban Polarization

The estimated model implies substantial changes in the allocation of jobs across space and their relative wages in response to increased IT usage. The impact of IT is however not limited to a reallocation of labor across cities and jobs, it also has an impact on city aggregates. In Figure 5 we show the change in city size, house prices and average wages in response to the fall in IT prices. The (relative) size of cities hardly responds to IT prices, while house prices and wages rise substantially and rise by more in initially expensive locations. Thus, our results are also consistent with the observed lack of convergence across cities in terms of average income over the last decades (Giannone, 2017).



(a) Size

(b) House price

(c) Average Wage

Figure 5: IT and City Outcomes

Discussion. While our approach isolates the effect of changing IT prices from the role of agglomeration externalities (see for example Baum-Snow et al. (2018); Rossi-Hansberg et al. (2019)), it remains silent on the role of changing agglomeration. Our setup features constant returns and fixed productivity factors, which precludes a change in agglomeration externalities resulting from the change of IT prices. We do allow the allocation of labor to cities to match the data and hence reflect these additional forces from agglomeration, yet implicit in our assumptions is that IT prices do not change those agglomeration forces. While we lack detailed data to separately identify agglomeration externalities and how they would change with IT prices, our mechanism does isolate the role of IT prices on factor demand. If agglomeration externalities were endogenous and affected by IT, then IT prices would indirectly affect productivity, which could strengthen the impact of IT prices. Our results are, therefore, a conservative estimate of the role of IT prices on the allocation of labor in space.

Of course, rent is distinct to agglomeration or TFP, as rent is an equilibrium price determined, among other things, by overall productivity. The only distinction we want to make is that agglomeration that has different productivity effects by job type could spuriously explain the sorting results. Thus, we are reassured by the fact that the changes in sorting happen along the price dimension and are not spuriously driven by comparing large and small cities, but by comparing cheap with expensive cities. This is the dimension along which our proposed mechanism works.

In Section 3 we have also shown indirect empirical evidence that agglomeration externalities do not affect the estimates of the elasticities of routine cognitive employment with respect to house prices. For IT usage we show the corresponding evidence in the appendix, in Tables A-20 and A-21 we add MSA employment size as a control for the cases with and without firm fixed effects. In both cases, results for the local price index are preserved. Differently, MSA employment size is statistically insignificant after controlling for local rental prices in the case without firm fixed effects, while having a small positive impact in the case with fixed effects. In line with the proposed mechanism, these results show that IT investment is higher in expensive cities, even when compared to similarly sized, cheaper cities.[26]

Given that in our calibration of the model IT can not explain *all* the changes in wages and employment over time and across cities, we highlight some other important factors here. These potentially also interact with IT usage. First, we have held constant the production technology in the counterfactual, as highlighted by Acemoglu and Restrepo (2022), among others, allowing technology to respond endogenously to the price of technology by expanding the number of tasks, would given an even more important role to technology. On top of that, other changes in the economy, in particular automation technology like robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Faia et al., 2022), and trade (Autor et al., 2016) have been shown to be important factors in explaining employment trends. Given the strong geographic concentration of the manufacturing sector, and the potential spatial impact of changes in trade technology (Ducruet et al., 2019), these are complementary mechanisms that affect not only the aggregate changes in employment, but also the distribution of jobs in space. Furthermore, the long-run effects of technology may also work through the interaction with labor supply by changing skill accumulation and education decisions as in Dvorkin and Monge-Naranjo (2019). Finally, the current paper is in

[26]Note that the size and the housing price of a city are not 1:1 related. The lack of a 1:1 relationship holds empirically, and also in our model due to skill-biased technological change and housing supply differences.

itself not intended to make predictions about the *future* impact of new technologies. However, such technologies like AI, will likely have not only an important impact on the allocation of labor across jobs, but also on the allocation of labor across space and will reshape cities in important ways. For example, in case new technologies can substitute non-routine cognitive workers, the impact of said technologies will likely not only lead to a substantial reallocation of workers from the jobs we labelled non-routine cognitive (Frank et al., 2019), but can also turn over the sorting patterns across space that have been dominant in the last decades. However, in order to make predictions in this direction one needs credible estimates of the substitution elasticity between different types of labor and *new* technologies.

5 Conclusion

Inequality through polarization has an important urban component, and this urban dimension is key in the investment decision of firms to adopt new technologies (IT). In this paper, we have used a novel data set about IT expenditure at the establishment level to establish two robust facts about urban polarization. We find, first, that IT investment is increasing in local housing costs, second, we find that there is a relatively larger decline in routine cognitive occupations in expensive cities. In addition, we document the evolution of wage inequality by occupation across cities with different housing costs.

We then use these facts to build and estimate an equilibrium model that elucidates the underlying mechanism of urban polarization. Workers locate in cities where the bundle of wages, housing prices, and amenities gives them the highest utility. This continuous arbitrage pins down equilibrium wages and prices for given productivity differences across cities. At these equilibrium wage and price bundles, the incentives for firms to invest in IT vary substantially across high-productivity cities with high wages and high housing prices and low-productivity cities with low wages and low housing prices. We find that IT investment and its implications for the allocation of jobs across cities depend crucially on the properties of the production technology.

There are substantial differences across cities in the impact of IT investment both on wage inequality and on the reallocation of routine tasks. The results from the estimated model indicate, that IT can explain 30 percent of the stronger displacement of routine cognitive jobs in expensive cities. This confirms that job polarization is a predominantly urban phenomenon that determines both the employment distribution between and within cities and inequality.

Appendix

Table of Contents

A Descriptive Statistics: Additional Description and Tables

A.1 Construction: Occupation Categories

Table A-1 shows the classification into groups by task components and the corresponding titles of occupation groups in the Census 2010 Occupation Classification system[27].

Table A-1: Occupation Groups by Tasks

Tasks	Census Occupations
Non-routine Cognitive	Management
	Business and financial operations
	Computer, Engineering and Science
	Education, Legal, Community Service, Arts and Media Occupations
	Healthcare Practitioners and Technical Occupations
Non-routine Manual	Service Occupations
Routine Cognitive	Sales and Related
	Office and Administrative Support
Routine Manual	Construction and Extraction
	Installation, Maintenance and Repair
	Production
	Transportation and Material Moving

Table A-2 presents sample averages and standard deviations in the subsample of MSAs for which we have data in all years in the census and information on technology adoption: occupation shares, employment levels, and our MSA rent index.

Table A-3 repeats the employment overview but splits the data into cheap and expensive cities, defined as the lowest and highest tercile of rents and highlights the differences in the decline of routine jobs across cities. We focus on the employment in routine-cognitive jobs, the jobs likely exposed to automation displacement driven by IT.

Figure A-1 shows employment shares by occupation across cities for 1990 and 2015. The figure shows that local housing prices and occupation shares follow an approximately log-linear relationship.

Table A-4 presents the summary statistics for IT budget per worker across MSAs. First, notice that there is a difference in the definition of the unit of count between the first row and rows 2-4 in Table A-4. In the first row, we calculate the MSA's IT budget per worker by dividing the sum of the total IT budget of all establishments in the MSA by the sum of these establishments' labor force. In this sense, we obtain an average IT budget per worker that puts more weight on larger

[27] See `https://www.census.gov/people/io/files/2010_OccCodeswithCrosswalkfrom2002-2011nov04.xls` for the detailed list of Census 2010 Occupations and Cortes et al. (2014) for the mapping to previous Census Occupation Classifications.

Table A-2: Descriptive statistics

	1990 mean (st. dev.)	2015 mean (st. dev.)
MSA's Occupation Shares		
Non-Routine Cognitive	33.03% (5.4)	39.98% (6.53)
Non-Routine Manual	10.69% (2.18)	14.89% (2.83)
Routine Cognitive	27.00% (2.70)	22.25% (2.23)
Routine Manual	28.60% (6.48)	22.16% (5.17)
MSA's Rent and Size		
log rent index	-0.34 (0.28)	-0.32 (0.25)
Employment in 000s	194.41 (450.99)	239.88 (532.58)
No. of MSAs	264	264

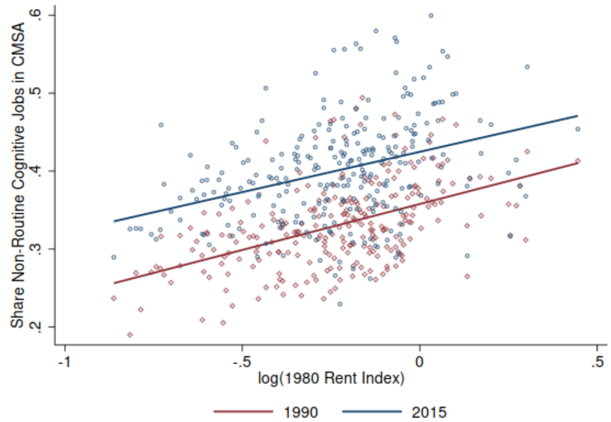
Note: Subsample of MSAs for which we have complete data in all years.

Table A-3: Descriptive Statistics: Occupations – Cheap vs. Expensive MSAs

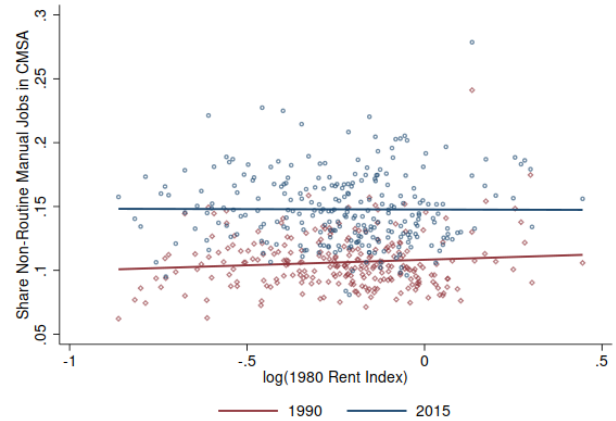
	1990		2015	
	Cheap	Expensive	Cheap	Expensive
Non-Routine Cognitive	30.16% (4.50)	35.76% (5.06)	37.59% (4.80)	42.77% (7.05)
Non-Routine Manual	10.56% (1.99)	10.67% (2.45)	15.17% (2.72)	14.81% (3.05)
Routine Cognitive	26.26% (2.68)	27.88% (2.52)	22.67% (2.07)	21.84%*** (2.50)
Routine Manual	32.47% (6.33)	25.01% (4.72)	24.16% (4.38)	19.67%*** (4.62)
Observations	86	85	86	85

Note: Subsample of MSAs for which we have complete data in all years. Cheap and expensive groups are comprised by MSAs in the first and the third tercile of the 1980's log(rent index) distribution, respectively. Values between parenthesis present the standard deviation of the mean. *** indicates that the difference in mean percentage change in the occupation share in cheap and expensive MSAs between the two time period is statistically significant at 1% according to a two-sample Wilcoxon rank-sum (Mann–Whitney) test.

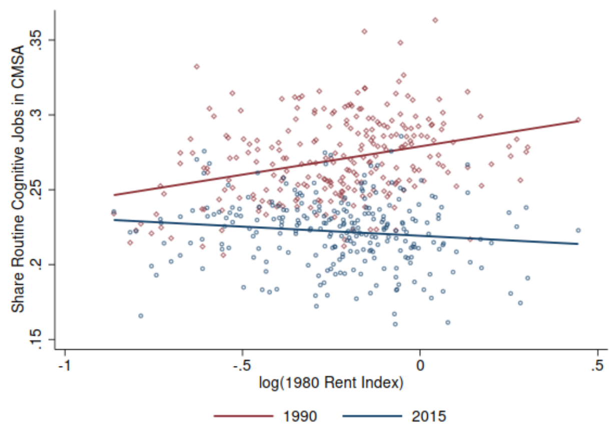
establishments. Differently, for the summary statistics presented in rows 2-4, we first calculate the IT budget per worker for each establishment and then look at the average, median, and standard deviation of IT budget per worker across establishments within a given MSA. Consequently, rows 2-4 have an establishment as the unit of measure, reducing the weight of larger establishments in the overall count. In this sense, rows 2-4 allow us to evaluate within- and between-MSA IT



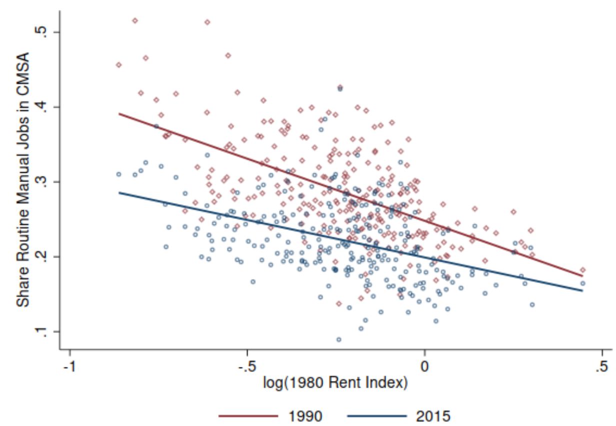
(a) Non-Routine Cognitive



(b) Non-Routine Manual



(c) Routine Cognitive



(d) Routine Manual

Figure A-1: Occupations across MSAs: 1980 vs. 2015

budget per worker dispersion across establishments. While our analysis focuses on the definition of MSA's IT budget per worker presented in Table A-4's row 1, rows 2-4 show that there is significant within-MSA variation of IT budget per worker across establishments. Moreover, our empirical results are robust to the different ways to calculate the IT budget per worker presented in Table A-4. As we can see in row 1 of Table A-4, there is significant variation in IT budget per worker across MSAs.

A.2 Adjusted IT Measures

Let $\lambda_{i,c,t}$ be the technology for establishment i in city c and time t. We estimate, using OLS, the following model:

$$\lambda_{i,c,t} = \sum_t \left[\beta_{I,t} Ind_{i,t} \times Size_{i,t} + \beta_{C,t} City_{i,t} + \beta_{Y,t} Year_{i,t}\right] + \varepsilon_{i,t} \tag{A.1}$$

Table A-4: Descriptive statistics of technology adoption across MSAs – 2015

	Mean	**Median**	**S.D.**	**Min**	**Max**	**N**
IT Budget						
MSA's IT Budget/Emp.	5,110	4,490	2,485	2,794	34,327	277
Avg. IT Budget/Emp. by site	4,244	4,162	530	3,293	6,326	277
Median IT Budget/Emp. by site	2,886	2,857	343	2,062	3,750	277
St. Dev. IT Budget/Emp. by site	9,057	4.963	12,061	3,123	97,557	277

where *Ind*, *Size*, and *City* are vectors of dummy variables of industry (3-digit SIC) of the establishment, size of the establishment (8 employment size classes, following CBP[28]). In this case, $\beta_{C,t}$ is the key measure, capturing the differences in technology use across cities, after controlling for over 950 industry/size interactions.

B Employment and Establishment Coverage: Comparison to CBP's Data

B.1 CBP Data

The County Business Patterns is an annual series that provides sub national economic data by industry. This series includes the number of establishments, employment during the week of March 12, first quarter payroll, and annual payroll. The CBP excludes from its data self-employed individuals (a lot of them are in the 1-3 establishment size categories), as well as contract or temporary employees, counting only "hired employees." While we don't have a detailed description of Aberdeen's employment data, we believe that it follows a similar pattern of the National Establishment Time Series (NETS) which uses Dun & Bradstreet data (D&B). As we see below, our comparison of the Aberdeen data with NETS corroborates this result. In the NETS, data contract and temporary workers are included, as well as self-employed workers.

Moreover, establishments in the following NAICS industries are not included in the CBP: Crop and Animal Production (NAICS 111, 112), Rail Transportation (NAICS 482), Postal Service (NAICS 491), Pension, Health, Wealfare, and Vacation Funds (NAICS 52110, 525120, 525190), Trust, Estates, and Agency Accounts (NAICS 525920), Private Households (NAICS 814), and Public Administration (NAICS 92).

Furthermore, the CBP defines establishments as *"a single physical location at which business is conducted or services or industrial operations are performed (...) with paid employees."*. Differently, in the NETS, an establishment is defined as a "unique line of business (SIC8) at a unique location."

[28]Doms and Lewis (2006) are not clear about which categories they are. However, since they weight their regression based on the CBP and limit their sample to establishments with 5 employees or more, the class sizes are likely: 5 to 9 employees,10 to 19 employees, 20 to 49 employees, 50 to 99 employees, 100 to 249 employees, 250 to 499 employees, 500 to 999 employees, and more than 1000 employees.

So, it is possible to have more than one establishment at a location. As Aberdeen uses DUNS numbers to identify establishments, it is likely that it follows NETS' definition.

Finally, in order to properly compare the industry×MSA composition of the employment and establishment data between CBP and Ci Aberdeen, we use the imputed CBP files for 2015 by Eckert et al. (2021). However, results are qualitatively the same if we use CBP's raw files.

B.2 Comparison to Ci Aberdeen Data: IT Budget Sample

In order to properly compare the two samples, we restrict the IT budget sample to private establishments in industries covered by the CBP. Furthermore, we aggregate the establishment and employment counts at the MSA level. Notice that while our sample covers on average only 34 percent of the MSA's establishments (table A-5), Table A-6 shows that this is mostly due to a low coverage of establishments with 1 to 4 employees. In fact, the coverage is on average above 60 percent for establishments with 10 employees or more. In contrast, our sample seems to have too many large establishments (500+). This is likely due to contract and temporary workers, which are not counted by the CBP. These patterns are in line with what Barnatchez et al. (2017) find when comparing NETS to the CBP, corroborating the idea that the Ci Aberdeen data have features similar to the NETS.

Table A-5: Coverage Ci Aberdeen relative to CBP

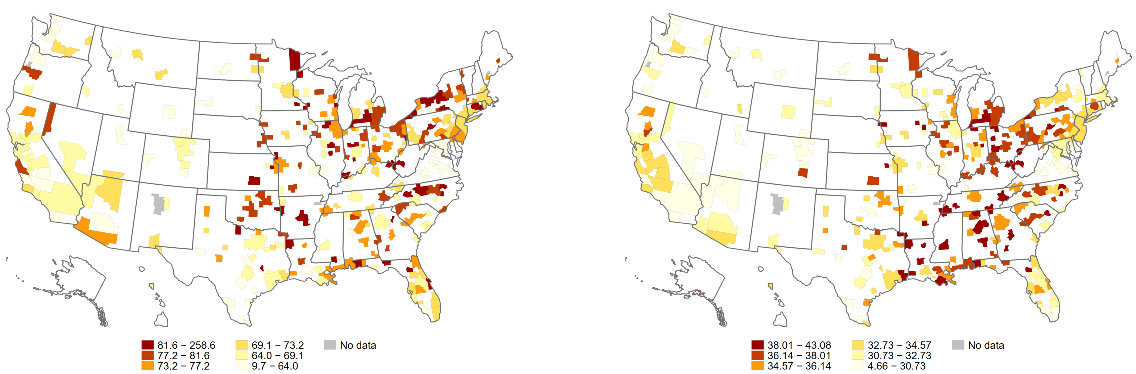
	Mean	**S.D.**	**p10**	**p25**	**p50**	**p75**	**p90**	**N**
IT Budget Sample								
Fraction Emp. in Ci	73%	16%	62%	66%	73%	79%	85%	277
Fraction Est. in Ci	34%	5%	29%	32%	35%	37%	39%	277
ERP Sample								
Fraction Emp. in Ci	25%	9%	16%	20%	25%	29%	33%	277
Fraction Est. in Ci	2%	1%	2%	2%	2%	3%	3%	277

In terms of industry coverage, we see that our sample has low coverage in leisure and hospitality, trade, transportation, and utility, as well as other services in both establishment and employment coverage (see Tables A-7 and A-8). On the other hand, our sample seems to overstate the employment in several sectors, in particular mining, manufacturing, and information. The excessive coverage in manufacturing and mining has also been documented in NETS by Barnatchez et al. (2017). Apart from the already mentioned differences in the types of employment covered by NETS (and probably Ci Aberdeen) and the CBP, another issue highlighted by Barnatchez et al. (2017) is the difficulty in industry assignment. Consequently, a significant share of the differences may be due not to measurement error, but to differences in industry assignment methods.

Finally, in terms of geographic coverage, the IT budget sample shows a higher coverage in the Midwest and East Coast regions, while coverage rates are somewhat lower in the West Coast and Western regions. Patterns are quite similar for both employment (figure A-2a) and establishments

Table A-6: Coverage Ci Aberdeen relative to CBP by establishment size

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
1 to 4 Employees	11%	2%	9%	10%	11%	13%	14%	277
5 to 9 Employees	45%	7%	38%	41%	45%	48%	53%	277
10 to 19 Employees	68%	9%	59%	63%	68%	73%	78%	277
20 to 49 Employees	63%	9%	55%	59%	64%	69%	73%	277
50 to 99 Employees	64%	11%	52%	59%	64%	71%	77%	277
100 to 249 Employees	74%	16%	58%	66%	73%	82%	93%	277
250 to 499 Employees	89%	29%	62%	71%	86%	100%	119%	277
500 to 999 Employees	115%	69%	60%	75%	100%	133%	200%	273
1,000 or more Employees	142%	94%	71%	100%	119%	167%	200	274
ERP Sample								
1 to 4 Employees	0%	0%	0%	0%	0%	0%	0%	277
5 to 9 Employees	0%	0%	0%	0%	0%	1%	1%	277
10 to 19 Employees	2%	1%	1%	1%	2%	2%	3%	277
20 to 49 Employees	6%	2%	4%	5%	6%	8%	9%	277
50 to 99 Employees	15%	5%	10%	12%	15%	18%	22%	277
100 to 249 Employees	32%	10%	22%	26%	31%	38%	45%	277
250 to 499 Employees	43%	19%	25%	32%	41%	50%	66%	277
500 to 999 Employees	66%	49%	25%	39%	54%	75%	120%	273
1,000 or more Employees	88%	66%	40%	53%	73%	100%	150%	274



(a) Employment Coverage

(b) Establishment Coverage

Figure A-2: Geographical distribution of Ci Coverage relative to CBP: IT Budget Sample

(figure A-2b). That said, coverage rates even in areas with low coverage are still meaningful (above 64 percent for employment and above 30 percent for establishments).

B.3 Comparison to Ci Aberdeen Data: ERP Sample

As discussed in Section 2, our ERP sample is limited. Our information on ERP adoption covers on average only 25 percent of workers and 2 percent of establishments in the MSA, compared to the

Table A-7: Ci Coverage relative to CBP: Establishments by industry

	Mean	**S.D.**	**p10**	**p25**	**p50**	**p75**	**p90**	**N**
IT Budget Sample								
Manufacturing	96%	18%	76%	85%	96%	107%	116%	277
Construction	26%	7%	17%	21%	25%	30%	35%	277
Information	84%	23%	63%	70%	80%	94%	110%	277
Finance	53%	11%	41%	45%	53%	60%	67%	277
Professional & Bus Services	34%	6%	27%	31%	35%	38%	42%	277
Education and Health	60%	11%	48%	54%	60%	66%	73%	277
Leisure and Hospitality	12%	3%	9%	10%	12%	14%	16%	277
Trade, Transp., and Util.	19%	3%	15%	18%	19%	21%	23%	277
Mining	66%	47%	21%	35%	56%	88%	117%	271
Other Services	18%	4%	14%	15%	18%	20%	22%	277
ERP Sample								
Manufacturing	12%	5%	6%	9%	13%	15%	18%	277
Construction	1%	1%	1%	1%	1%	2%	2%	277
Information	9%	4%	4%	7%	8%	11%	14%	277
Finance	1%	1%	1%	1%	1%	2%	2%	277
Professional & Bus Services	2%	1%	1%	2%	2%	3%	4%	277
Education and Health	4%	1%	2%	3%	4%	5%	5%	277
Leisure and Hospitality	1%	1%	1%	1%	1%	2%	2%	277
Trade, Transp., and Util.	1%	1%	1%	1%	1%	2%	2%	277
Mining	6%	10%	0%	0%	2%	8%	14%	271
Other Services	1%	1%	1%	1%	1%	2%	2%	277

CBP (see Table A-5). Moreover, as presented in Table A-6, even after controlling for establishment size, MSA average coverage is above 30 percent only for establishments that have 100 employees or more. Finally, Table A-7 shows that the ERP sample covers less than 15 percent of establishments in all industry sectors. However, since the coverage is tilted towards larger establishments, employment coverage varies from 8 (Leisure and Hospitality) to 56 percent (Manufacturing), as we can see in Table A-8.

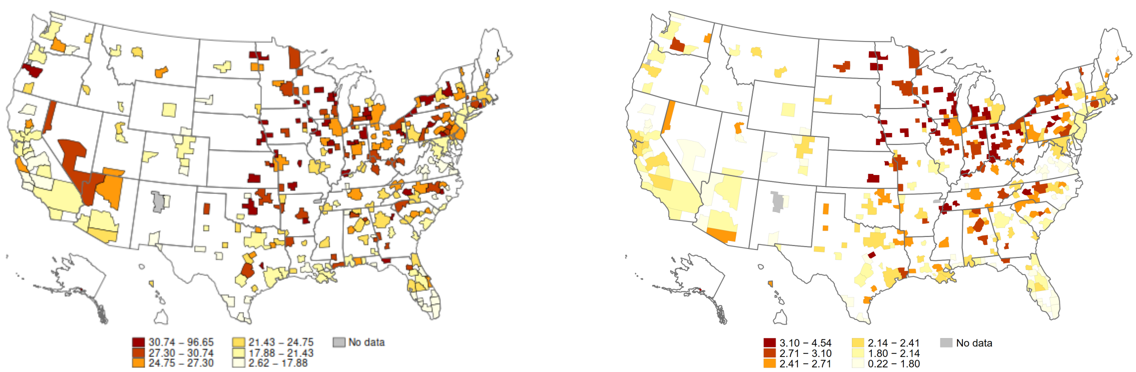
Finally, in terms of geographic coverage, the ERP sample shows a higher coverage in the Midwest and East Coast regions, while coverage rates are somewhat lower in the West Coast and Western regions. Patterns are quite similar for both employment (Figure A-3a) and establishments (Figure A-3b). That said, coverage rates even in areas with low coverage are still meaningful.

C Comparison ICT Investment – Aberdeen vs. BEA data

We now compare the Aberdeen ICT data to the detailed data for fixed assets and consumer goods from the Bureau of Economic Analysis (BEA). In particular, we compare the 2015 IT budget information from Aberdeen to the information in the BEA's 2015 investment table at the detailed

Table A-8: Ci Coverage relative to CBP: Employment by industry

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
Manufacturing	129%	48%	86%	102%	123%	145%	168%	277
Construction	87%	28%	61%	70%	84%	98%	115%	277
Information	126%	69%	68%	90%	115%	141%	179%	277
Finance	98%	27%	70%	83%	97%	111%	129%	277
Professional & Bus Services	69%	27%	47%	55%	63%	77%	96%	277
Education and Health	104%	62%	71%	85%	97%	114%	133%	277
Leisure and Hospitality	25%	12%	14%	17%	22%	28%	36%	277
Trade, Transp., and Util.	45%	10%	34%	39%	45%	50%	55%	277
Mining	178%	392%	14%	55%	104%	192%	326%	277
Other Services	64%	37%	41%	47%	57%	68%	90%	277
ERP Sample								
Manufacturing	56%	24%	29%	42%	54%	68%	80%	277
Construction	12%	11%	3%	7%	10%	15%	22%	277
Information	43%	35%	16%	25%	36%	53%	69%	277
Finance	18%	13%	4%	8%	16%	25%	37%	277
Professional & Bus Services	15%	13%	5%	9%	13%	19%	26%	277
Education and Health	45%	31%	24%	32%	43%	51%	63%	277
Leisure and Hospitality	8%	8%	2%	3%	6%	10%	15%	277
Trade, Transp., and Util.	10%	6%	4%	6%	9%	13%	17%	277
Mining	34%	120%	0%	0%	1%	31%	72%	277
Other Services	16%	30%	3%	7%	11%	16%	26%	277



(a) Employment Coverage (b) Establishment Coverage

Figure A-3: Geographical distribution of Ci coverage relative to CBP: ERP sample

estimates by industry and by type of assets.[29] For the investment data from the BEA, we consider the ICT assets presented in table A-9. In table A-11, we compare the total values for Aberdeen and BEA per industry sector. We must keep in mind that the variables in Aberdeen and BEA don't line up perfectly. Aberdeen's IT budget represents Aberdeen's best guess on establishment's *planned*

[29]See details here.

budget to invest in ICT assets. In contrast, BEA's private fixed investment measures *spending* by private business on fixed assets in the U.S. economy. Nevertheless, values in BEA and Aberdeen are reasonably close. First, aggregate IT budget values in Aberdeen represent close to 70% of the total investment in ICT assets by the private sector in NIPA. Furthermore, as we see in table A-10, the distribution of ICT investment across sectors is similar in both databases, apart from a few caveats. In particular, Aberdeen ICT information has a higher incidence on Professional services and Education & Health than BEA, while having a lower incidence on Information and FIRE. In fact, the ICT budget and expenditure totals presented in table A-11 corroborate the results from table A-10, with the share of total BEA investment detected in Aberdeen being significantly lower for the Information and FIRE sectors. That said, the correlation in terms of either sector's ICT investment levels or share of total ICT in the sector between BEA and Aberdeen is above 0.7.

Table A-9: ICT Assets in BEA Investment Aggregate

Asset Code	**NIPA Asset Type**
EP1A	Mainframes
EP1B	PCs
EP1C	DASDs
EP1D	Printers
EP1E	Terminals
EP1F	Tape drives
EP1G	Storage devices
EP1H	System integrators
EP20	Communications
ENS1	Prepackaged software
ENS2	Custom software
ENS3	Own account software
RD23	Semiconductor and other component manufacturing
RD21	Computers and peripheral equipment manufacturing
RD22	Communications equipment manufacturing
RD25	Other computer and electronic manufacturing, n.e.c.
RD40	Software publishers

D Empirical Evidence - Alternative technology measures

D.1 Enterprise Resource Planning (ERP) software

In this section, we discuss the empirical evidence on the relationship between ERP adoption and local rental price index as well as 1980's share of routine cognitive jobs in the local labor force.

Table A-10: ICT Investment: Industry Distribution

Industry Sector	% of total investment	
	Aberdeen	**BEA**
Mining	0.76	0.49
Utilities	2.31	1.4
Construction	1.91	0.89
Manufacturing	21.23	16.79
Wholesale Trade	5.54	3.91
Retail Trade	1.56	4.08
Transportation	2.04	1.85
Information	12.41	30.95
Professional Services	24.57	15.58
FIRE	10.13	17.24
Education & Health	10.61	4.47
Leisure & Hospitality	3.9	1.08
Other Services	3.03	1.26

Table A-11: ICT Investment: BEA vs. Aberdeen

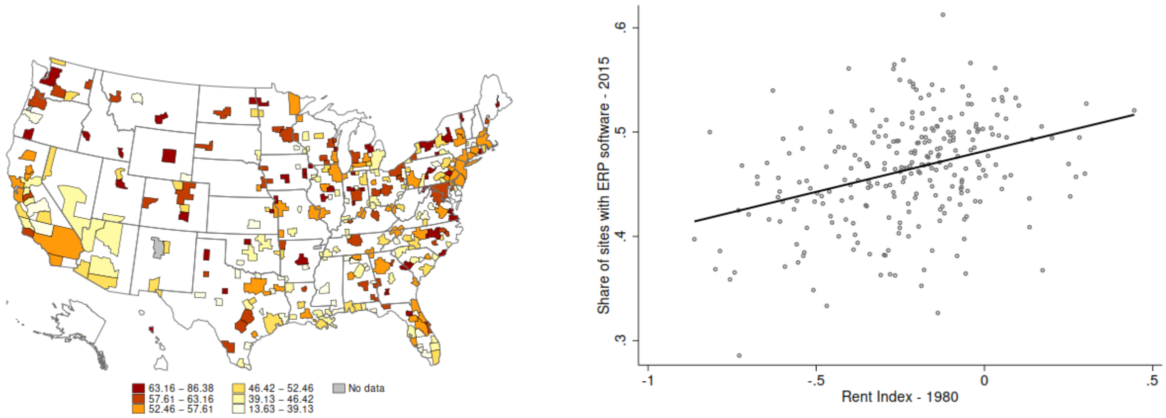
Industry Sector	ICT Investment ($ millions)		% Aberdeen in BEA
	Aberdeen	**BEA**	
Mining	3,170	3,054	104
Utilities	9,599	8,649	111
Construction	7,932	5,530	143
Manufacturing	88,245	103,910	85
Wholesale Trade	23,029	24,184	95
Retail Trade	6,470	25,216	26
Transportation	8,477	11,471	74
Information	51,574	191,461	27
Professional Services	102,099	96,393	106
FIRE	42,113	106,688	39
Education & Health	44,099	27,677	159
Leisure & Hospitality	16,223	6,665	243
Other Services	12,578	7,813	161
Total Economy	**415,608**	**618,711**	**67**

D.2 Descriptive Statistics

Table A-12 shows that there is a lot of dispersion in the ERP shares across MSAs even in 2015, when we should expect a more widespread use of technology. As we can see, we have at least some information on 277 MSAs across the country. Moreover, we can see that, while on average about 46 percent of the establishments have at least some form of ERP, there is substantial variation across the country. Some MSAs have a fraction as low as 29 percent, while others have more than 61 percent of establishments with some form of ERP. Even more, as we show in Figure A-4b, the degree of adoption seems closely tied to the size as well as cost of living in the MSA, proxied by the rental index. Finally, figure A-4a shows the geographical dispersion of ERP concentration across the country in 2015. First, geographical coverage is quite good, with only very few MSAs completely missing. In fact, the missing MSAs are due to the procedure for matching the census PUMA to the 2000 census metropolitan area definitions as described by Baum-Snow and Pavan (2013).

Table A-12: Descriptive statistics of technology adoption across MSAs – 2015

	Mean	Median	S.D.	Min	Max	N
ERP Share						
Share of Workers in Est. w/ ERP	51.49%	52.42%	12.45%	13.63%	86.38%	277
Share of Establishments w/ ERP	46.39%	46.67%	5.08%	28.57%	61.25%	277
No. of ERPs						
Avg. No. of ERPs per Est.	0.77	0.78	0.11	0.41	1.17	277
Median No. of ERPs per Est.	0.24	0	0.42	0	1.00	277
St. Dev. of No. ERP per Est.	1.05	1.06	0.11	0.73	1.36	277



(a) Share of workers exposed to ERP

(b) ERP share vs. local price level

Figure A-4: Geographical distribution of ERP across MSAs – 2015

D.3 Empirical Results

Table A-13 presents the same specifications as presented in Table 1, replacing IT budget per worker with the fraction of establishments in the MSA with at least one ERP software. As we can observe, results for local price indexes are similar to the ones observed in Table 1, i.e., establishments in more expensive areas are more likely to have at least one installed ERP software. In particular, in specification (5), a one standard deviation increase in the local price index (an increase of 21.4 percent in the 1980 local price index) is associated with an increase of about 1 percent in the share of establishments with ERP. In fact, moving from the cheapest to the most expensive MSA is associated with a 5 percent increase in the share of establishments in the MSA with at least one ERP software installed.

Table A-14 presents the results for a logit model on the presence of an installed ERP software in the establishment, after controlling for firm and industry fixed effects. Controls are the same as presented in Table A-15. As expected, due to a significant decrease in sample size, results are weaker and lose statistical significance in some cases. However, the overall pattern is still the same as the one presented in Table A-15, i.e., establishments in more expensive MSAs are more likely to adopt ERP software.

Table A-13: Share of Establishments with ERP – 2015

	(1)	(2)	(3)	(4)	(5)	(6)
	ERP Share	ERP Share	ERP Share	ERP Share	ERP Share	ERP Share
MSA log rent index 1980	0.076***	0.062***			0.050*	0.050*
	(0.015)	(0.023)			(0.028)	(0.028)
MSA RC share 1980			0.297*		0.337**	0.353**
			(0.158)		(0.159)	(0.166)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.026*	-0.000	-0.000
				(0.015)	(0.018)	(0.018)
MSA Offshorability 1980						-0.021
						(0.061)
Housing supply elasticity		0.002	0.003	0.000	0.002	0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	25.87	7.82	5.77	7.67	7.69	7.45
Adj. R^2	0.113	0.373	0.255	0.359	0.383	0.381
MSAs	218	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the share of establishments with at least one ERP software in the metro area. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-14: ERP presence by establishment - Firm and industry FE

	ERP Dummy				
	(1)	(2)	(3)	(4)	(5)
MSA log rent index 1980	0.249			0.340*	0.347*
	(0.175)			(0.198)	(0.199)
MSA routine cognitive share 1980		0.037***		0.039***	0.041***
		(0.014)		(0.014)	(0.015)
MSA's log $\left(\frac{S}{U}\right)$ in 1980			-0.030	-0.224	-0.218
			(0.130)	(0.150)	(0.150)
MSA Offshorability 19800					-0.223
					(0.447)
log(Site's Size)	0.254***	0.254***	0.254***	0.254***	0.254***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
log(Site's Revenue)	0.307***	0.308***	0.307***	0.308***	0.308***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Headquarters dummy	1.135***	1.134***	1.135***	1.133***	1.133***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Housing supply elasticity	0.029	0.013	0.019	0.020	0.022
	(0.021)	(0.020)	(0.021)	(0.022)	(0.022)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
MSA Controls	Yes	Yes	Yes	Yes	Yes
No. of Sites	31,451	31,451	31,451	31,451	31,451
No. of Firms	4,318	4,318	4,318	4,318	4,318
No. of MSAs	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the a dummy variable that indicates the presence of at least one ERP software in the establishment. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are 2-digit SIC dummies. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E Additional Reduced-Form Empirical Results

E.1 Introducing Firm Fixed effects on Establishment Regressions

Table A-15: IT Investment by Establishment – Firm and Industry Fixed Effects

	log(IT)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980	0.434***	0.322***	0.097***			0.110***	0.108***
	(0.058)	(0.042)	(0.024)			(0.030)	(0.030)
MSA RC share 1980				0.004*		0.004*	0.003
				(0.002)		(0.002)	(0.002)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.018	-0.029	-0.030
					(0.018)	(0.021)	(0.022)
MSA Offshorability 1980							0.064
							(0.071)
log(Site's Size)		-0.003	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(Site's Revenue)		2.839***	2.131***	2.131***	2.131***	2.131***	2.131***
		(0.070)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Headquarters dummy		-0.046***	0.042***	0.042***	0.042***	0.041***	0.041***
		(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Housing elasticity			0.000	-0.004	-0.003	-0.000	-0.001
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	56.16	596.77	1,324.54	1,388.42	1,402.49	1,338.21	1,332.14
Adj. R^2	0.0089	0.4216	0.7683	0.7682	0.7682	0.7683	0.7683
No. of Sites	267,180	261,488	142,072	142,072	142,072	142,072	142,072
No. of Firms	131,400	131,333	19,141	19,141	19,141	19,141	19,141
No. of MSAs	262	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Each observation (an establishment) is weighted by the probability weight from a match between the Aberdeen data and the 2015 County Business Patterns. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are two-digit SIC dummies. We cluster standard errors at the MSA level. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E.2 Changes in Occupation Shares

In this section, we present the changes over time of different occupation classes, based on the classification presented by Cortes et al. (2014). Our specification includes the same controls as the ones presented in Table 3.

Based on the results for Tables A-16, A-17, and A-18, we see that cost of living is not correlated to changes in these occupation categories in the period 1990-2015. Results from these tables corroborate our findings in Online Appendix Section B.1, in which location quotients do not show a significant change in the concentration across cities of different costs for all but routine cognitive occupations.

Table A-16: Change in non-routine cognitive share, 1990-2015

	Δnonrout-cog					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	-0.0172	-0.0008			-0.0276	-0.0276
	(0.0107)	(0.0214)			(0.0225)	(0.0226)
MSA RC share 1980			0.2667**		0.2395**	0.2291*
			(0.1207)		(0.1175)	(0.1316)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0220*	0.0240*	0.0240*
				(0.0118)	(0.0123)	(0.0123)
MSA Offshorability 1980						0.0116
						(0.0497)
Housing supply elasticity		-0.0014	-0.0009	-0.0008	-0.0013	-0.0013
		(0.0016)	(0.0014)	(0.0014)	(0.0015)	(0.0015)
F statistic	2.60	4.99	5.11	4.82	4.97	4.92
Adj. R^2	0.007	0.289	0.309	0.303	0.314	0.311
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of non-routine cognitive occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E.3 Introducing MSA size as a control

Table A-17: Change in routine manual share, 1990-2015

	Δrout-man					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.0617***	0.0549***			0.0513**	0.0514**
	(0.0107)	(0.0195)			(0.0221)	(0.0221)
MSA RC share 1980			0.1000		0.0161	0.0315
			(0.1284)		(0.1298)	(0.1326)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0203*	0.0039	0.0040
				(0.0115)	(0.0132)	(0.0133)
MSA Offshorability 1980						-0.0173
						(0.0471)
Housing supply elasticity		0.0048***	0.0031*	0.0034**	0.0048***	0.0048**
		(0.0018)	(0.0017)	(0.0017)	(0.0018)	(0.0018)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	33.31	5.66	5.02	5.10	5.20	5.07
Adj. R^2	0.143	0.318	0.287	0.295	0.311	0.308
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of routine manual occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-18: Change in non-routine manual share, 1990-2015

	Δnonrout-man					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	-0.0113	-0.0209*			-0.0113	-0.0113
	(0.0072)	(0.0124)			(0.0143)	(0.0144)
MSA RC share 1980			-0.0424		0.0097	0.0093
			(0.0768)		(0.0789)	(0.0856)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				-0.0163**	-0.0130	-0.0130
				(0.0070)	(0.0082)	(0.0082)
MSA Offshorability 1980						0.0005
						(0.0267)
Housing supply elasticity		-0.0020	-0.0014	-0.0017	-0.0020	-0.0020
		(0.0015)	(0.0014)	(0.0014)	(0.0015)	(0.0015)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	2.43	4.71	4.76	5.23	4.68	4.61
Adj. R^2	0.011	0.209	0.195	0.217	0.212	0.207
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of non-routine manual occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-19: IT budget per worker – 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)
MSA log rent index 1980	0.125***		0.133***			0.109**	0.110**
	(0.021)		(0.042)			(0.045)	(0.044)
log employment 1980		0.017***	-0.001			-0.000	-0.000
		(0.005)	(0.007)			(0.007)	(0.007)
MSA RC share 1980				0.594**		0.400	0.466
				(0.291)		(0.318)	(0.343)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.0579**	0.013	0.012
					(0.0269)	(0.030)	(0.030)
MSA Offshorability 1980							-0.077
							(0.108)
Housing supply elasticity			0.003	0.000	0.0004	0.003	0.003
			(0.004)	(0.004)	(0.0038)	(0.004)	(0.004)
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
MSA's Industry Mix Controls	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	35.38	11.71	15.09	14.01	14.92	14.47	14.09
Adj. R^2	0.097	0.040	0.374	0.360	0.359	0.374	0.376
MSAs	218	218	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the metro area, adjusted for plant employment interacted with three-digit NAICS industry. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-20: IT Investment by Establishment

	log(IT)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980						0.095***	0.094***
						(0.031)	(0.031)
MSA log employment 1980	0.065***	0.043***	0.009**			0.002	0.001
	(0.008)	(0.006)	(0.004)			(0.004)	(0.004)
MSA RC share 1980				0.002		0.000	-0.000
				(0.002)		(0.002)	(0.002)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.055***	0.019	0.018
					(0.019)	(0.021)	(0.021)
MSA Offshorability 1980							0.072
							(0.064)
log(Site's Size)		-0.004	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***
		(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Site's Revenue)		2.837***	2.558***	2.558***	2.558***	2.557***	2.557***
		(0.069)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Headquarters dummy		-0.045***	0.001	0.001	0.001	0.000	0.000
		(0.009)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Housing elasticity			-0.005	-0.008*	-0.006	-0.002	-0.003
			(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	72.93	610.49	20,707.32	20,340.62	16,888.61	22,166.37	21,831.45
Adj. R^2	0.0087	0.4204	0.7138	0.7138	0.7138	0.7139	0.7139
No. of Sites	267,180	261,488	247,933	247,933	247,933	247,933	247,933
No. of Firms	131,333	131,333	125,002	125,002	125,002	125,002	125,002
No. of MSAs	262	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Each observation (an establishment) is weighted by the probability weight from a match between the Aberdeen data and the 2015 County Business Patterns. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are twp-digit SIC dummies. We cluster standard errors at the MSA level. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-21: IT Investment by Establishment – Firm and Industry Fixed Effects

	log(IT)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980						0.079**	0.079**
						(0.033)	(0.033)
MSA log employment 1980	0.065***	0.043***	0.018***			0.014***	0.013***
	(0.008)	(0.006)	(0.004)			(0.005)	(0.005)
MSA RC share 1980				0.004*		0.003*	0.003
				(0.002)		(0.002)	(0.002)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.018	-0.025	-0.026
					(0.018)	(0.021)	(0.021)
MSA Offshorability 1980							0.026
							(0.071)
log(Site's Size)		-0.004	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(Site's Revenue)		2.837***	2.131***	2.131***	2.131***	2.131***	2.131***
		(0.069)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Headquarters dummy		-0.045***	0.042***	0.042***	0.042***	0.041***	0.041***
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Housing elasticity			0.001	-0.004	-0.003	0.002	0.002
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	72.93	610.49	1,373.36	1,388.42	1,402.49	1,383.31	1,367.87
Adj. R^2	0.0087	0.4204	0.7683	0.7682	0.7682	0.7683	0.7683
No. of Sites	267,180	261,488	142,072	142,072	142,072	142,072	142,072
No. of Firms	131,333	131,333	19,141	19,141	19,141	19,141	19,141
No. of MSAs	262	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are twp-digit SIC dummies. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-22: IT Investment by Establishment

	log(IT)					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.443***	0.209***			0.194***	0.193***
	(0.059)	(0.040)			(0.047)	(0.047)
MSA RC share 1980			0.001		-0.002	-0.002
			(0.003)		(0.003)	(0.003)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.093***	0.028	0.027
				(0.029)	(0.032)	(0.032)
MSA Offshorability 1980						0.037
						(0.105)
Headquarters dummy	-0.049***	-0.023***	-0.023***	-0.023***	-0.023***	-0.023***
	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Housing Elasticity		0.004	-0.005	-0.003	0.004	0.004
		(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Industry FE	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	28.01	5,932.41	6,003.35	6,479.30	5,970.62	5,929.08
Adj. R^2	0.0096	0.5117	0.5114	0.5115	0.5117	0.5117
No. of Sites	261,636	248,068	248,068	248,068	248,068	248,068
No. of Firms	131,333	125,002	125,002	125,002	125,002	125,002
No. of MSAs	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Each observation (an establishment) is weighted by the probability weight from a match between the Aberdeen data and the 2015 County Business Patterns. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are two-digit SIC dummies. We cluster standard errors at the MSA level. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-23: IT Investment by Establishment – Firm and Industry Fixed Effects

	log(IT)					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.443***	0.148***			0.195***	0.196***
	(0.059)	(0.042)			(0.049)	(0.049)
MSA RC share 1980			-0.001		-0.001	-0.001
			(0.004)		(0.004)	(0.004)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				-0.003	-0.070**	-0.070**
				(0.029)	(0.033)	(0.032)
MSA Offshorability 1980						-0.029
						(0.117)
Headquarters dummy	-0.049***	0.136***	0.136***	0.136***	0.136***	0.136***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Housing elasticity		0.010	0.004	0.004	0.010*	0.010*
		(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	28.01	775.70	696.55	708.21	759.68	753.64
Adj. R^2	0.0096	0.6096	0.6096	0.6096	0.6097	0.6097
No. of Sites	261,636	142,163	142,163	142,163	142,163	142,163
No. of Firms	131,400	19,159	19,159	19,159	19,159	19,159
No. of MSAs	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Each observation (an establishment) is weighted by the probability weight from a match between the Aberdeen data and the 2015 County Business Patterns. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are two-digit SIC dummies. We cluster standard errors at the MSA level. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-24: IT Investment by Establishment

	log(IT)					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980					0.187***	0.187***
					(0.048)	(0.048)
MSA log employment 1980	0.066***	0.015**			0.003	0.003
	(0.008)	(0.007)			(0.007)	(0.007)
MSA RC share 1980			0.001		-0.002	-0.002
			(0.003)		(0.003)	(0.003)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.093***	0.029	0.028
				(0.029)	(0.032)	(0.032)
MSA Offshorability 1980						0.029
						(0.108)
Headquarters dummy	-0.048***	-0.023***	-0.023***	-0.023***	-0.023***	-0.023***
	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Housing elasticity		-0.001	-0.005	-0.003	0.005	0.004
		(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Industry FE	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	38.01	6,030.07	6,003.35	6,479.30	6,027.00	5,976.87
Adj. R^2	0.0094	0.5114	0.5114	0.5115	0.5117	0.5117
No. of Sites	261,636	248,068	248,068	248,068	248,068	248,068
No. of Firms	131,400	125,064	125,064	125,064	125,064	125,064
No. of MSAs	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Each observation (an establishment) is weighted by the probability weight from a match between the Aberdeen data and the 2015 County Business Patterns. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are twp-digit SIC dummies. We cluster standard errors at the MSA level. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-25: IT Investment by Establishment – Firm and Industry Fixed Effects

	log(IT)					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980					0.169***	0.169***
					(0.054)	(0.053)
MSA log employment 1980	0.066***	0.020***			0.012	0.013
	(0.008)	(0.007)			(0.008)	(0.008)
MSA RC share 1980			-0.001		-0.001	-0.001
			(0.004)		(0.004)	(0.004)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				-0.003	-0.067**	-0.065**
				(0.029)	(0.032)	(0.032)
MSA Offshorability 1980						-0.065
						(0.118)
Headquarters dummy	-0.048***	0.136***	0.136***	0.136***	0.136***	0.136***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Housing elasticity		0.009	0.004	0.004	0.012**	0.012**
		(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	38.01	842.90	696.55	708.21	863.69	850.22
Adj. R^2	0.0094	0.6096	0.6096	0.6096	0.6097	0.6097
No. of Sites	261,636	142,163	142,163	142,163	142,163	142,163
No. of Firms	131,400	19,159	19,159	19,159	19,159	19,159
No. of MSAs	262	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the establishment. Establishment controls include establishment size and revenue based on the Ci Technology data and a corporate headquarter dummy based on NETS data. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Industry dummies are twp-digit SIC dummies. Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-26: Share of Establishments with ERP – 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ERP Share	ERP Share	ERP Share	ERP Share	ERP Share	ERP Share	ERP Share
MSA log rent index 1980	0.076***		0.063***			0.051*	0.051*
	(0.015)		(0.023)			(0.028)	(0.028)
log employment 1980		0.010***	-0.002			-0.002	-0.002
		(0.003)	(0.004)			(0.004)	(0.004)
MSA RC share 1980				0.297*		0.333**	0.349**
				(0.158)		(0.159)	(0.165)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.026*	-0.000	-0.000
					(0.015)	(0.018)	(0.018)
MSA Offshorability 1980							-0.019
							(0.060)
Housing supply elasticity			0.001	0.003	0.000	0.002	0.002
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	25.87	13.89	7.80	5.77	7.67	7.68	7.36
Adj. R^2	0.113	0.043	0.370	0.255	0.359	0.381	0.378
MSAs	218	218	218	218	218	218	218

Standard errors in parentheses. The dependent variable in all columns is the share of establishments with at least one ERP software in the metro area. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-27: Change in routine-cognitive share, 1990-2015

				Δrout-cog			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980	-0.0427***		-0.0467***			-0.0292**	-0.0293**
	(0.0076)		(0.0117)			(0.0122)	(0.0122)
log employment 1980		-0.0089***				0.0012	0.0014
		(0.0014)				(0.0022)	(0.0022)
MSA RC share 1980				-0.2881***		-0.2109***	-0.1972**
				(0.0752)		(0.0752)	(0.0799)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					-0.0275***	-0.0129	-0.0128
					(0.0076)	(0.0086)	(0.0086)
MSA Offshorability 1980							-0.0151
							(0.0271)
Housing supply elasticity			-0.0016	-0.0008	-0.0010	-0.0017	-0.0017
			(0.0014)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	31.36	42.31	11.08	11.41	11.96	11.31	10.87
Adj. R^2	0.122	0.132	0.511	0.511	0.508	0.538	0.537
MSAs	211	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of routine cognitive occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-28: Change in routine manual share, 1990-2015

	Δrout-man						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980	0.0617***		0.0607***			0.0577**	0.0577**
	(0.0107)		(0.0200)			(0.0223)	(0.0223)
log employment 1980		0.0024	-0.0075**			-0.0075**	-0.0074**
		(0.0019)	(0.0032)			(0.0032)	(0.0032)
MSA RC share 1980				0.1000		0.0091	0.0150
				(0.1284)		(0.1306)	(0.1313)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.0203*	0.0034	0.0034
					(0.0115)	(0.0128)	(0.0129)
MSA Offshorability 1980							-0.0066
							(0.0486)
Housing supply elasticity			0.0034*	0.0031*	0.0034**	0.0034*	0.0034*
			(0.0018)	(0.0017)	(0.0017)	(0.0019)	(0.0019)
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	33.31	1.65	5.70	5.02	5.10	5.38	5.22
Adj. R^2	0.143	0.001	0.333	0.287	0.295	0.326	0.323
MSAs	211	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of routine manual occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-29: Change in non-routine cognitive share, 1990-2015

	Δnonrout-cog						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980	-0.0172 (0.0107)		-0.0069 (0.0215)			-0.0347 (0.0220)	-0.0347 (0.0221)
log employment 1980		0.0064*** (0.0021)	0.0080** (0.0031)			0.0083*** (0.0030)	0.0083*** (0.0031)
MSA RC share 1980				0.2667** (0.1207)		0.2473** (0.1148)	0.2477* (0.1263)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					0.0220* (0.0118)	0.0246** (0.0123)	0.0246** (0.0124)
MSA Offshorability 1980							-0.0004 (0.0504)
Housing supply elasticity			0.0001 (0.0018)	-0.0009 (0.0014)	-0.0008 (0.0014)	0.0002 (0.0017)	0.0002 (0.0017)
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	2.60	9.76	6.69	5.11	4.82	6.91	6.69
Adj. R^2	0.007	0.035	0.306	0.309	0.303	0.334	0.331
MSAs	211	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of non-routine cognitive occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A-30: Change in non-routine manual share, 1990-2015

	Δnonrout-man						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSA log rent index 1980	-0.0113		-0.0206			-0.0109	-0.0109
	(0.0072)		(0.0126)			(0.0146)	(0.0146)
log employment 1980		-0.0000	-0.0004			-0.0004	-0.0005
		(0.0011)	(0.0020)			(0.0020)	(0.0020)
MSA routine cognitive share 1980				-0.0424		0.0093	0.0083
				(0.0768)		(0.0788)	(0.0855)
MSA's log $\left(\frac{S}{U}\right)$ in 1980					-0.0163**	-0.0131	-0.0131
					(0.0070)	(0.0083)	(0.0083)
MSA Offshorability 1980							0.0011
							(0.0267)
Housing supply elasticity			-0.0021	-0.0014	-0.0017	-0.0021	-0.0021
			(0.0017)	(0.0014)	(0.0014)	(0.0016)	(0.0016)
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	No	Yes	Yes	Yes	Yes	Yes
CMSA Controls	No	No	Yes	Yes	Yes	Yes	Yes
F statistic	2.43	0.00	4.57	4.76	5.23	4.59	4.57
Adj. R^2	0.011	-0.005	0.205	0.195	0.217	0.208	0.203
MSAs	211	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of non-routine manual occupations in the MSA's employed labor force between 1990 and 2015. MSA controls include its unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work states. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

F Theoretical Results

Closing the Model The final steps to close the model involve simplifying the model such that we have a system with only two equations and two unknowns (k_1 and $\frac{p_1}{p_2}$). Based on the calculations presented in the paper for k_2, k_1 and their respective FOCs, we obtain:

$$F_j(m_{1j}, m_{2j}, m_{3j}, k_j) = A_j \left[m_{1j}^{\lambda_1} A_{l,1} + \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k \right)^{\frac{\lambda_2}{\gamma}} + m_{3j}^{\lambda_3} A_{l,3} \right] \tag{A.2}$$

FOCs:

$$\begin{aligned}
&(m_{1j}) : A_j \lambda_1 m_{1j}^{\lambda_1 - 1} A_{l,1} = w_{1j} \\
&(m_{2j}) : A_j \lambda_2 \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k \right)^{\frac{\lambda_2}{\gamma} - 1} m_{2j}^{\gamma - 1} A_{l,2} = w_{2j} \\
&(m_{3j}) : A_j \lambda_3 m_{3j}^{\lambda_3 - 1} A_{l,3} = w_{3j} \\
&(k_j) : A_j \lambda_2 \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k \right)^{\frac{\lambda_2}{\gamma} - 1} k_j^{\gamma - 1} A_k = r
\end{aligned}$$

Since from utility equalization, we have:

$$\frac{w_{ij}}{w_{ij'}} = \left(\frac{p_j}{p_{j'}} \right)^{\alpha}, \quad \forall i \in \{1, 2, 3\} \text{ and } \forall j \in \{1, 2\} \tag{A.3}$$

From (m_{11}), (m_{12}), and the feasibility condition for skill 1, we have:

$$m_{11} = \frac{\left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{1}{\lambda_1 - 1}} M_1}{1 + \left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{1}{\lambda_1 - 1}}} \tag{A.4}$$

Similarly, for skill 3:

$$m_{31} = \frac{\left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{1}{\lambda_3 - 1}} M_3}{1 + \left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{1}{\lambda_3 - 1}}} \tag{A.5}$$

From (m_{21}), (k_1), (m_{22}), (k_2), labor market clearing, and the utility equalization condition, we have:

$$\left(\frac{m_{21}}{m_{22}} \right) = \left(\frac{p_1}{p_2} \right)^{\frac{\alpha}{\gamma - 1}} \frac{k_1}{k_2} \tag{A.6}$$

Now let's go back to the expression for (k_1). Manipulating it, we have that:

$$m_{21} = \left\{ \frac{1}{A_{l,2}} \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1 - \lambda_2)}{\lambda_2 - \gamma}} - A_k \right] \right\}^{\frac{1}{\gamma}} k_1 \tag{A.7}$$

Similarly, for (k_2), we have:

$$m_{22} = \left\{ \frac{1}{A_{l,2}} \left[\left(\frac{r}{A_2 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_2^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right] \right\}^{\frac{1}{\gamma}} k_2 \tag{A.8}$$

Dividing (A.7) by (A.8)and substituting (A.6), we have:

$$\left(\frac{p_1}{p_2} \right)^{\frac{\alpha\gamma}{\gamma - 1}} = \left\{ \frac{\left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]}{\left[\left(\frac{r}{A_2 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_2^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]} \right\} \tag{A.9}$$

Manipulating and simplifying it, we have:

$$k_2^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} = \left(\frac{A_2}{A_1} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} \left(\frac{p_1}{p_2} \right)^{\frac{\alpha\gamma}{1-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} + \left(\frac{r}{A_2 \lambda_2 A_k} \right)^{\frac{\gamma}{\gamma - \lambda_2}} \left[1 - \left(\frac{p_1}{p_2} \right)^{\frac{\alpha\gamma}{1-\gamma}} \right] A_k$$

Now, we also can use the fact that $m_{21} + m_{22} = M_2$. Then, we have that:

$$M_2 A_{l,2}^{\frac{1}{\gamma}} = \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} k_1 + \left[\left(\frac{r}{A_2 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_2^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} k_2 \tag{A.10}$$

Substituting (A.9) and manipulating, we have:

$$k_2 = \frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} k_1}{\left(\frac{p_1}{p_2} \right)^{\frac{\alpha}{1-\gamma}} \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}} \tag{A.11}$$

Substituting (A.11) into (A.10) and manipulating, we have:

$$\begin{aligned} &\left\{ \frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} k_1}{\left(\frac{p_1}{p_2} \right)^{\frac{\alpha}{1-\gamma}} \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}} \right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} = \\ &= \left(\frac{A_2}{A_1} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} \left(\frac{p_1}{p_2} \right)^{\frac{\alpha\gamma}{1-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} + \left(\frac{r}{A_2 \lambda_2 A_k} \right)^{\frac{\gamma}{\gamma - \lambda_2}} \left[1 - \left(\frac{p_1}{p_2} \right)^{\frac{\alpha\gamma}{1-\gamma}} \right] A_k \end{aligned} \tag{A.12}$$

which implicitly pins down k_1 as a function of $\frac{p_1}{p_2}$.

Finally, in order to pin down the equilibrium, we need to work with the housing market equilibrium conditions. Looking at the ratio of the housing market clearing conditions, we have:

$$\frac{w_{11}m_{11}+w_{21}m_{21}+w_{31}m_{31}}{w_{12}m_{12}+w_{22}m_{22}+w_{32}m_{32}}=\frac{p_1}{p_2}$$

Now substituting for the wage and labor demand and rearranging it, we have:

$$\begin{aligned}&\left\{\begin{array}{c}\left(m_{21}^{\gamma}A_{l,2}+k_1^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}m_{21}^{\gamma}A_{l,2}-\\-\frac{A_2}{A_1}\frac{p_1}{p_2}\left(m_{22}^{\gamma}A_{l,2}+k_2^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}m_{22}^{\gamma}A_{l,2}\end{array}\right\}=\\&\left\{\begin{array}{c}\left(\frac{M_1}{1+\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_1-1}}}\right)^{\lambda_1}A_{l,1}\left[\frac{A_2}{A_1}\frac{p_1}{p_2}-\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{\lambda_1}{\lambda_1-1}}\right]\\+\left(\frac{M_3}{1+\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_3-1}}}\right)^{\lambda_3}A_{l,3}\left[\frac{A_2}{A_1}\frac{p_1}{p_2}-\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{\lambda_3}{\lambda_3-1}}\right]\end{array}\right\}\end{aligned}\tag{A.13}$$

Then, from the ratio of (m_{21}) and (m_{22}), we have:

$$\left(m_{22}^{\gamma}A_{l,2}+k_2^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}=\left(\frac{p_2}{p_1}\right)^{\alpha}\left(m_{21}^{\gamma}A_{l,2}+k_1^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}\times\left(\frac{m_{21}}{m_{22}}\right)^{\gamma-1}\times\left(\frac{A_1}{A_2}\right)\tag{A.14}$$

Substituting (A.14) into (A.13) and rearranging, we have:

$$\begin{aligned}&\left\{\left[1-\left(\frac{p_1}{p_2}\right)^{1-\alpha}\frac{M_2-m_{21}}{m_{21}}\right]\left(m_{21}^{\gamma}A_{l,2}+k_1^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}m_{21}^{\gamma}A_{l,2}\right\}=\\&\left\{\begin{array}{c}\left(\frac{M_1}{1+\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_1-1}}}\right)^{\lambda_1}A_{l,1}\left[\frac{A_2}{A_1}\frac{p_1}{p_2}-\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{\lambda_1}{\lambda_1-1}}\right]\\+\left(\frac{M_3}{1+\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_3-1}}}\right)^{\lambda_3}A_{l,3}\left[\frac{A_2}{A_1}\frac{p_1}{p_2}-\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{\lambda_3}{\lambda_3-1}}\right]\end{array}\right\}\end{aligned}\tag{A.15}$$

But then, from equation (A.7), we have that:

$$m_{21}^{\gamma}A_{l,2}=\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\gamma)}{\lambda_2-\gamma}}-k_1^{\gamma}A_k\tag{A.16}$$

Similarly, from (k_1), we have:

$$\left(m_{21}^{\gamma}A_{l,2}+k_1^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}=\left(\frac{r}{A_1\lambda_2A_k}\right)k_1^{1-\gamma}\tag{A.17}$$

Then, from (A.16) and (A.17), we have:

$$\left(m_{21}^{\gamma}A_{l,2}+k_1^{\gamma}A_k\right)^{\frac{\lambda_2-\gamma}{\gamma}}m_{21}^{\gamma}A_{l,2}=\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\lambda_2}{\lambda_2-\gamma}}k_1^{\frac{\lambda_2(1-\gamma)}{\lambda_2-\gamma}}-\frac{r}{A_1\lambda_2}k_1\tag{A.18}$$

Substituting equation (A.11) into (A.6) and manipulating, we have:

$$\frac{M_2 - m_{21}}{m_{21}} = \frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}}{k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}} \tag{A.19}$$

Consequently:

$$\left[1 - \left(\frac{p_1}{p_2} \right)^{1-\alpha} \frac{M_2 - m_{21}}{m_{21}} \right] = \frac{\left\{ \begin{array}{c} \left(1 + \left(\frac{p_1}{p_2} \right)^{1-\alpha} \right) k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} \\ - \left(\frac{p_1}{p_2} \right)^{1-\alpha} M_2 A_{l,2}^{\frac{1}{\gamma}} \end{array} \right\}}{k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}} \tag{A.20}$$

Then, from equations (A.18) and (A.20), we have that:

$$\begin{gathered} \left[1 - \left(\frac{p_1}{p_2} \right)^{1-\alpha} \frac{M_2 - m_{21}}{m_{21}} \right] \left(m_{21}^{\gamma} A_{l,2} + k_1^{\gamma} A_k \right)^{\frac{\lambda_2 - \gamma}{\gamma}} m_{21}^{\gamma} A_{l,2} = \\ \frac{\left\{ \begin{array}{c} \left(1 + \left(\frac{p_1}{p_2} \right)^{1-\alpha} \right) k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} \\ - \left(\frac{p_1}{p_2} \right)^{1-\alpha} M_2 A_{l,2}^{\frac{1}{\gamma}} \end{array} \right\}}{k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}} \times \left\{ \left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\lambda_2}{\lambda_2 - \gamma}} k_1^{\frac{\lambda_2(1-\gamma)}{\lambda_2 - \gamma}} - \frac{r}{A_1 \lambda_2} k_1 \right\} \end{gathered} \tag{A.21}$$

Notice that the LHS of equation (A.21) is the same as the LHS of equation (A.15). Substituting it back, we have:

$$\begin{gathered} \frac{\left\{ \begin{array}{c} \left(1 + \left(\frac{p_1}{p_2} \right)^{1-\alpha} \right) k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}} \\ - \left(\frac{p_1}{p_2} \right)^{1-\alpha} M_2 A_{l,2}^{\frac{1}{\gamma}} \end{array} \right\}}{k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k \right]^{\frac{1}{\gamma}}} \times \left\{ \left(\frac{r}{A_1 \lambda_2 A_k} \right)^{\frac{\lambda_2}{\lambda_2 - \gamma}} k_1^{\frac{\lambda_2(1-\gamma)}{\lambda_2 - \gamma}} - \frac{r}{A_1 \lambda_2} k_1 \right\} = \\ \left\{ \begin{array}{c} \left(\frac{M_1}{1 + \left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{1}{\lambda_1 - 1}}} \right)^{\lambda_1} A_{l,1} \left[\frac{A_2}{A_1} \frac{p_1}{p_2} - \left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{\lambda_1}{\lambda_1 - 1}} \right] \\ + \left(\frac{M_3}{1 + \left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{1}{\lambda_3 - 1}}} \right)^{\lambda_3} A_{l,3} \left[\frac{A_2}{A_1} \frac{p_1}{p_2} - \left[\frac{A_2}{A_1} \left(\frac{p_1}{p_2} \right)^{\alpha} \right]^{\frac{\lambda_3}{\lambda_3 - 1}} \right] \end{array} \right\} \end{gathered} \tag{A.22}$$

Finally, notice that equations (A.22) and (A.12) generate a system with two equations and two unknowns (k_1 and $\frac{p_1}{p_2}$):

$$\left\{\begin{array}{l}
\dfrac{\left\{\begin{array}{c}\left(1+\left(\frac{p_1}{p_2}\right)^{1-\alpha}\right) k_1\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}\\ -\left(\frac{p_1}{p_2}\right)^{1-\alpha} M_2A_{l,2}^{\frac{1}{\gamma}}\end{array}\right\}}{k_1\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}\times\left\{\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\lambda_2}{\lambda_2-\gamma}} k_1^{\frac{\lambda_2(1-\gamma)}{\lambda_2-\gamma}}-\frac{r}{A_1\lambda_2}k_1\right\}=\\
\qquad\left\{\begin{array}{l}\left(\dfrac{M_1}{1+\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_1-1}}}\right)^{\lambda_1}A_{l,1}\left[\frac{A_2}{A_1}\frac{p_1}{p_2}-\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{\lambda_1}{\lambda_1-1}}\right]\\ +\left(\dfrac{M_3}{1+\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_3-1}}}\right)^{\lambda_3}A_{l,3}\left[\frac{A_2}{A_1}\frac{p_1}{p_2}-\left[\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{\lambda_3}{\lambda_3-1}}\right]\end{array}\right\} \qquad (F.1)\\
\left\{\dfrac{M_2A_{l,2}^{\frac{1}{\gamma}}-\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}k_1}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}\right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}= \qquad (F.2)\\
=\left(\frac{A_2}{A_1}\right)^{\frac{\gamma}{\lambda_2-\gamma}}\left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{1-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}+\left(\frac{r}{A_2\lambda_2A_k}\right)^{\frac{\gamma}{\gamma-\lambda_2}}\left[1-\left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{1-\gamma}}\right]A_k
\end{array}\right.$$

Preliminary Results We start by presenting some preliminary results that will help us to show the main results presented in the paper.

Lemma A.1: *The distribution of skills across cities is identical if and only if* $\frac{m_{i1}}{m_{i2}} = constant, \forall i \in \{1,2,3\}$.

Proof: ($\Rightarrow$) Consider that the distribution across cities is constant, then $pdf_{i1} = pdf_{i2}, \forall i \in \{1,2,3\}$, i.e.:

$$\frac{m_{i1}}{m_{11}+m_{21}+m_{31}} = \frac{m_{i2}}{m_{12}+m_{22}+m_{32}} \tag{A.23}$$

But that means that $\frac{m_{i1}}{m_{i2}} = \eta = \frac{S_1}{S_2} = \frac{m_{11}+m_{21}+m_{31}}{m_{12}+m_{22}+m_{32}}$. The other direction is trivial. ■

Lemma A.2: *Assume* $\lambda_2 < \gamma$. $p_1 = p_2$ *if and only if* $A_1 = A_2$.

Proof: Towards a contradiction, let's assume that $A_1 = A_2$ and $p_1 > p_2$. From the RHS of (F.1), we have:

$$\left\{\begin{array}{l}\left(\dfrac{M_1}{1+\left[\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_1-1}}}\right)^{\lambda_1}A_{l,1}\left[\frac{p_1}{p_2}-\left(\frac{p_1}{p_2}\right)^{\frac{\lambda_1\alpha}{\lambda_1-1}}\right]\\ +\left(\dfrac{M_3}{1+\left[\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_3-1}}}\right)^{\lambda_3}A_{l,3}\left[\frac{p_1}{p_2}-\left(\frac{p_1}{p_2}\right)^{\frac{\lambda_3\alpha}{\lambda_3-1}}\right]\end{array}\right\}>0$$

Since $p_1 > p_2$, $\lambda_1 < 1$, and $\lambda_3 < 1$. Therefore, the LHS of (F.1) must also be positive in order for the equality to be satisfied. Then, from equation (A.18), we have:

$$(m_{21}^{\gamma}A_{l,2}+k_1^{\gamma}A_k)^{\frac{\lambda_2-\gamma}{\gamma}}\,m_{21}^{\gamma}A_{l,2}=\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\lambda_2}{\lambda_2-\gamma}}k_1^{\frac{\lambda_2(1-\gamma)}{\lambda_2-\gamma}}-\frac{r}{A_1\lambda_2}k_1$$

So the second term on the LHS of $(F.1)$ must be positive. Moreover, from (A.17), we have that:

$$k_1\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}=m_{21}A_{l,2}^{\frac{1}{\gamma}}>0$$

Consequently, in order to satisfy $(F.1)$, we must have:

$$\frac{M_2A_{l,2}^{\frac{1}{\gamma}}-k_1\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}{\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}<k_1\left(\frac{p_1}{p_2}\right)^{\alpha-1}$$

Dividing both sides by $\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}$, we have:

$$\frac{M_2A_{l,2}^{\frac{1}{\gamma}}-k_1\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}<k_1\left(\frac{p_2}{p_1}\right)^{\left(1+\frac{\alpha\gamma}{1-\gamma}\right)} \tag{A.24}$$

Now, from $(F.2)$, we have that, due to $p_1>p_2$ and $\lambda_2<\gamma$:

$$\frac{M_2A_{l,2}^{\frac{1}{\gamma}}-k_1\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}}k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}}-A_k\right]^{\frac{1}{\gamma}}}>\left(\frac{p_2}{p_1}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}}k_1 \tag{A.25}$$

Then, notice that:

$$1+\frac{\alpha\gamma}{1-\gamma}-\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}=1+\frac{\alpha\gamma}{1-\gamma}\left[1-\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}\right]=1+\frac{\alpha\gamma}{1-\gamma}\left[\frac{\lambda_2(1-\gamma)}{\gamma(1-\lambda_2)}\right]>0 \tag{A.26}$$

Therefore the exponent at $\frac{p_2}{p_1}$ is higher on the RHS of (A.24). Since $\frac{p_2}{p_1}\in(0,1)$, we have that:

$$k_1\left(\frac{p_2}{p_1}\right)^{\left(1+\frac{\alpha\gamma}{1-\gamma}\right)}<\left(\frac{p_2}{p_1}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}}k_1$$

Consequently, equations (A.24) and (A.25) give us a contradiction.

Now, again towards a contradiction, let's assume $p_2 > p_1$. In this case, from the RHS of $(F.1)$, we have:

$$\left\{ \begin{array}{c} \left(\frac{M_1}{1+\left[\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_1-1}}}\right)^{\lambda_1} A_{l,1}\left[\frac{p_1}{p_2}-\left(\frac{p_1}{p_2}\right)^{\frac{\lambda_1\alpha}{\lambda_1-1}}\right] \\ +\left(\frac{M_3}{1+\left[\left(\frac{p_1}{p_2}\right)^{\alpha}\right]^{\frac{1}{\lambda_3-1}}}\right)^{\lambda_3} A_{l,3}\left[\frac{p_1}{p_2}-\left(\frac{p_1}{p_2}\right)^{\frac{\lambda_3\alpha}{\lambda_3-1}}\right] \end{array} \right\} < 0$$

Since $p_1 < p_2$, $\lambda_1 < 1$, and $\lambda_3 < 1$. Therefore, the LHS of $(F.1)$ must also be negative. Since we already showed that the second term in the LHS and the denominator of the first term in the LHS must be positive, this requirement of a negative LHS implies, after dividing both sides by $\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}$:

$$\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}} > k_1\left(\frac{p_2}{p_1}\right)^{\left(1+\frac{\alpha\gamma}{1-\gamma}\right)} \tag{A.27}$$

Then, from $(F.2)$, since $p_1 < p_2$, the last term on the RHS is positive. Consequently, once $\lambda_2 < \gamma$, we have:

$$\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}} < \left(\frac{p_2}{p_1}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}} k_1 \tag{A.28}$$

Since:

$$1+\frac{\alpha\gamma}{1-\gamma}-\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)} = 1+\frac{\alpha\gamma}{1-\gamma}\left[1-\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}\right] = 1+\frac{\alpha\gamma}{1-\gamma}\left[\frac{\lambda_2(1-\gamma)}{\gamma(1-\lambda_2)}\right] > 0$$

and $p_2 > p_1$, we have that:

$$k_1\left(\frac{p_2}{p_1}\right)^{\left(1+\frac{\alpha\gamma}{1-\gamma}\right)} > \left(\frac{p_2}{p_1}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}} k_1$$

Consequently, equations (A.27) and (A.28) give us a contradiction. Therefore, we have that $p_1 = p_2 \Leftrightarrow A_1 = A_2$. ■

F.1 Proofs

Proof of Proposition 1

Proof. Towards a contradiction, assume that $A_2 > A_1$ and $p_1 > p_2$. Then, the RHS of $(F.1)$ is positive. Consequently, in order to satisfy $(F.1)$, $(F.1)$'s LHS must also be positive. Following the same argument presented in the proof of Lemma A.2, we have that inequality (A.24) must hold. Then, from $(F.2)$ we have that, given that $p_1 > p_2$, the last term in $(F.2)$'s RHS – $\left(\frac{r}{A_2\lambda_2 A_k}\right)^{\frac{\gamma}{\gamma-\lambda_2}}\left[1-\left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{1-\gamma}}\right]A_k$ – is negative. We also know that since $A_2 > A_1$ and $\lambda_2 < \gamma$, $\left(\frac{A_2}{A_1}\right)^{\frac{\gamma}{\lambda_2-\gamma}} < 1$. Therefore, $(F.2)$ gives us:

$$\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}} > \left(\frac{p_2}{p_1}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda_2}{\gamma(1-\lambda_2)}} k_1 \tag{A.29}$$

Given (A.26) we have that, once $\frac{p_2}{p_1} \in (0,1)$:

$$k_1\left(\frac{p_2}{p_1}\right)^{\left(1+\frac{\alpha\gamma}{1-\gamma}\right)} < \left(\frac{p_2}{p_1}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\frac{\gamma-\lambda}{\gamma(1-\lambda)}} k_1$$

Consequently, (A.24) and (A.29) give us a contradiction. Following the same procedure we can easily show that $A_1 > A_2$ and $p_2 > p_1$ give us the same contradiction. Since lemma A.1 shows that price equality is only achieved through TFP equality, this concludes our proof. ■

Proof of Proposition 2

Proof. Without loss of generality, assume $A_1 > A_2$, Then, based on proposition 1, we have that $p_1 > p_2$. Then, from equation (A.9), we have:

$$\left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{\gamma-1}} = \left[\frac{\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k}{\left(\frac{r}{A_2\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_2^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k}\right] \tag{A.30}$$

Then, since $\gamma < 1$, we have $\left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{\gamma-1}} < 1$. Consequently:

$$\left[\frac{\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k}{\left(\frac{r}{A_2\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_2^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k}\right] < 1 \tag{A.31}$$

Rearranging it:

$$\left(\frac{k_1}{k_2}\right)^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} < \left(\frac{A_1}{A_2}\right)^{\frac{\gamma}{\lambda_2-\gamma}} \tag{A.32}$$

Since $\lambda_2 < \gamma$, this implies that $\left(\frac{k_1}{k_2}\right)^{\frac{\gamma(1-\lambda_2)}{\gamma-\lambda_2}} > \left(\frac{A_1}{A_2}\right)^{\frac{\gamma}{\gamma-\lambda_2}}$. Since $A_1 > A_2$, we must have that $\frac{k_1}{k_2} > \frac{A_1}{A_2} \Rightarrow k_1 > k_2$. ■

Before we prove Theorem 1, let's prove some preliminary results that will be important for the theorems' proofs.

Lemma 2 *If $A_1 > A_2$ we must have that* $\left(\frac{p_2}{p_1}\right)^{\alpha}\frac{A_1}{A_2} > 1$.

Proof. From proposition 1 we have that $A_1 > A_2 \Rightarrow p_1 > p_2$. Now, let's focus on $(F.1)$'s RHS. This term is positive or negative depending on the following term:

$$\frac{A_2}{A_1}\frac{p_1}{p_2} - \left[\left(\frac{p_2}{p_1}\right)^{\alpha}\frac{A_1}{A_2}\right]^{\frac{\lambda_i}{1-\lambda_i}},\ \forall i \in \{1,3\} \tag{A.33}$$

Now, towards a contradiction, let's assume that $A_1 > A_2$ and $\left(\frac{p_2}{p_1}\right)^{\alpha}\frac{A_1}{A_2} \leq 1$. Consequently, the second term in expression (A.33) is less than one. Similarly, $\left(\frac{p_2}{p_1}\right)^{\alpha}\frac{A_1}{A_2} \leq 1 \Rightarrow \frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha} \geq 1$. Since $\alpha < 1$ and $\frac{p_1}{p_2} > 1$, this gives us that

$$\frac{A_2}{A_1}\frac{p_1}{p_2} - \left[\left(\frac{p_2}{p_1}\right)^{\alpha}\frac{A_1}{A_2}\right]^{\frac{\lambda_i}{1-\lambda_i}} > 0,\ \forall i \in \{1,3\}$$

and $(F.1)$'s RHS is positive.[30] Then, $(F.1)$'s LHS must also be positive. Following the same argument presented in the proof of lemma A.2, we have that inequality (A.24) must hold.

Similarly, from $p_1 > p_2$, we have that the last term on $(F.2)$'s RHS is negative. Therefore, since $\lambda_2 < \gamma$, we have:

$$\left\{\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - \left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}} k_1}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}}\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}\right\} > \left(\frac{A_2}{A_1}\right)^{\frac{1}{1-\lambda_2}}\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}\times\frac{\lambda_2-\gamma}{(1-\lambda_2)}} k_1 \tag{A.34}$$

Then, we have that:

$$\frac{\text{RHS(A.24)}}{\text{RHS(A.34)}} = \left(\frac{p_2}{p_1}\right)^{1+\frac{\alpha\gamma}{1-\gamma}\left[1-\frac{\lambda_2-\gamma}{\gamma(1-\lambda_2)}\right]}\left(\frac{A_1}{A_2}\right)^{\frac{1}{1-\lambda_2}} \tag{A.35}$$

Notice that $1 - \frac{\lambda_2-\gamma}{\gamma(1-\lambda_2)} = \frac{\lambda_2(1-\gamma)}{\gamma(1-\lambda_2)}$. Consequently:

$$\frac{\text{RHS(A.24)}}{\text{RHS(A.34)}} = \left(\frac{p_2}{p_1}\right)^{1+\frac{\lambda_2\alpha}{(1-\lambda_2)}}\left(\frac{A_1}{A_2}\right)^{\frac{1}{1-\lambda_2}} = \left\{\left(\frac{p_2}{p_1}\right)^{1-\lambda_2(1-\alpha)}\frac{A_1}{A_2}\right\}^{\frac{1}{1-\lambda_2}} \tag{A.36}$$

But then, notice that $1-\lambda_2(1-\alpha)-\alpha = (1-\alpha)(1-\lambda_2) > 0$. Therefore, $1-\lambda_2(1-\alpha) > \alpha$.

[30] Notice that the inequality is strictly positive, even if $\left(\frac{p_2}{p_1}\right)^{\alpha}\frac{A_1}{A_2} = 1$. In fact, in this case $\frac{A_2}{A_1}\frac{p_2}{p_1} = \left(\frac{A_1}{A_2}\right)^{\frac{1-\alpha}{\alpha}} > 1$.

Since $p_2 < p_1$, we have that:

$$\left(\frac{p_2}{p_1}\right)^{1-\lambda_2(1-\alpha)} \frac{A_1}{A_2} < \left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2} < 1 \tag{A.37}$$

where the last inequality comes from our assumption for the contradiction. Then, since $\frac{1}{1-\lambda_2} > 0$, we have $\frac{\text{RHS}(\text{A.24})}{\text{RHS}(\text{A.34})} < 1$. But then inequalities (A.24) and (A.34) cannot both be satisfied and we have a contradiction. ■

Corollary 2 *If $A_1 > A_2$ we must have $m_{11} > m_{12}$ and $m_{31} > m_{32}$.*

Proof. From the expression for m_{11}, we have:

$$m_{11} = \frac{\left[\left(\frac{p_1}{p_2}\right)^{\alpha} \frac{A_2}{A_1}\right]^{\frac{1}{\lambda_1 - 1}} M_1}{\left\{1 + \left[\left(\frac{p_1}{p_2}\right)^{\alpha} \frac{A_2}{A_1}\right]^{\frac{1}{\lambda_1 - 1}}\right\}} = \frac{\left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda_1}} M_1}{\left\{1 + \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda_1}}\right\}} \tag{A.38}$$

Since from lemma 2 we have $\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2} > 1$, we must have that $\frac{\left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda_1}} M_1}{\left\{1+\left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda_1}}\right\}} > \frac{M_1}{2}$. Consequently $m_{11} > m_{12}$. The identical argument shows that $m_{31} > m_{32}$. ■

Proof of Theorem 1

Proof. We already know that $m_{11} > m_{12}$ and $m_{31} > m_{32}$. So, the only way in which we may have $S_2 > S_1$ is that $m_{22} > m_{21}$. Therefore, towards a contradiction, assume that $m_{22} > m_{21}$. From (A.19):

$$\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1 \left[\left(\frac{r}{A_1 \lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k\right]^{\frac{1}{\gamma}}}{\left[\left(\frac{r}{A_1 \lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k\right]^{\frac{1}{\gamma}}} > k_1 \tag{A.39}$$

Then, back to $(F.2)$, we have:

$$\left\{\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - \left[\left(\frac{r}{A_1 \lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k\right]^{\frac{1}{\gamma}} k_1}{\left(\frac{p_1}{p_2}\right)^{\frac{\alpha}{1-\gamma}} \left[\left(\frac{r}{A_1 \lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2 - \gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} - A_k\right]^{\frac{1}{\gamma}}}\right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} =$$
$$= \left(\frac{A_2}{A_1}\right)^{\frac{\gamma}{\lambda_2 - \gamma}} \left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{1-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2 - \gamma}} + \left(\frac{r}{A_2 \lambda_2 A_k}\right)^{\frac{\gamma}{\gamma - \lambda_2}} \left[1 - \left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{1-\gamma}}\right] A_k \tag{A.40}$$

Since $A_1 > A_2$ we know from previous results that $p_1 > p_2$. Consequently, the last term in

$(F.2)$'s RHS is negative and we have:

$$\left\{\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - \left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}} k_1}{\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}\right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} > \left(\frac{A_2}{A_1}\right)^{\frac{\gamma}{\lambda_2-\gamma}} \left(\frac{p_1}{p_2}\right)^{\frac{\alpha\gamma}{1-\gamma}\times\left[1+\frac{1-\lambda_2}{\lambda_2-\gamma}\right]} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} \tag{A.41}$$

Now, from (A.39) we have that, since $\lambda_2 < \gamma$:

$$\left\{\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}{\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}\right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} < k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} \tag{A.42}$$

Now, substituting (A.42) into (A.41), we have:

$$k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} > \left\{\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - k_1\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}{\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}\right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} > \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{\gamma}{\gamma-\lambda_2}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} \tag{A.43}$$

From lemma 2 and the fact that $\gamma > \lambda_2$, we have that $\left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{\gamma}{\gamma-\lambda_2}} > 1$. Consequently, we found a contradiction. Therefore, we must have $m_{21} > m_{22}$ and $S_1 > S_2$. ■

Before presenting the proof for theorem 2, let's consider a final intermediary result:

Claim 1 *Assume $\lambda_2 < \gamma$. If $A_1 > A_2$ we must have* $\frac{m_{21}}{m_{22}} < \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda_2}}$

Proof. From lemma 2, we have that if $A_1 > A_2$ we must have $\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2} > 1$. Then, from $(F.2)$, since $p_1 > p_2$, we must have:

$$\left\{\frac{M_2 A_{l,2}^{\frac{1}{\gamma}} - \left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}} k_1}{k_1\left[\left(\frac{r}{A_1\lambda_2 A_k}\right)^{\frac{\gamma}{\lambda_2-\gamma}} k_1^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} - A_k\right]^{\frac{1}{\gamma}}}\right\}^{\frac{\gamma(1-\lambda_2)}{\lambda_2-\gamma}} < \left\{\frac{A_2}{A_1}\left(\frac{p_1}{p_2}\right)^{\alpha}\right\}^{\frac{\gamma}{\lambda_2-\gamma}}$$

From (A.19) and $\lambda_2 < \gamma$, we have $\frac{m_{21}}{m_{22}} < \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda_2}}$, concluding the proof. ■

Proof of Theorem 2:

Proof. Assume that $\lambda_i \equiv \lambda, \forall i \in \{1,2,3\}$ and $\lambda < \gamma$. Assume that $A_1 > A_2$ as well. From theorem 1 and claim 1 we have $S_1 < \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda}} S_2$. Then, notice that $pdf_{1i} = \frac{m_1 i}{S_i}$. Therefore $\frac{pdf_{11}}{pdf_{12}} = \frac{m_{11}}{m_{12}} \times \frac{S_2}{S_1}$. Since $\frac{m_{11}}{m_{12}} = \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda}}$ and $\frac{S_2}{S_1} > \frac{1}{\left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda}}}$, we have that:

$$\frac{pdf_{11}}{pdf_{12}} > \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda}} \times \frac{1}{\left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda}}} \tag{A.44}$$

Consequently $pdf_{11} > pdf_{12}$. The same calculation gives us $pdf_{31} > pdf_{32}$. Since density functions must add to one, we must also have $pdf_{21} < pdf_{22}$ ■

Proof of Corollary 1

Proof. From the proof of Proposition 2 and $\lambda_i \equiv \lambda,\ \forall i \in \{1,2,3\}$, we have that:

$$\left(\frac{k_1}{k_2}\right)^{\frac{\gamma(1-\lambda)}{\gamma-\lambda}} > \left(\frac{A_1}{A_2}\right)^{\frac{\gamma}{\gamma-\lambda}}$$

Rearranging it, we have:

$$\frac{k_1}{k_2} > \left(\frac{A_1}{A_2}\right)^{\frac{1}{1-\lambda}} \tag{A.45}$$

While from the proof of Theorem 2, we have:

$$\frac{S_1}{S_2} < \left[\left(\frac{p_2}{p_1}\right)^{\alpha} \frac{A_1}{A_2}\right]^{\frac{1}{1-\lambda}} \tag{A.46}$$

From Proposition 1, given $A_1 > A_2$, we have that $p_2 < p_1$. Consequently, from inequalities (A.45) and (A.46), we have:

$$\frac{k_1}{k_2} > \frac{S_1}{S_2} \Rightarrow \frac{k_1}{S_1} > \frac{k_2}{S_2} \tag{A.47}$$

concluding our proof. ■

Proof of Lemma 1

Proof. We consider the production function presented in equation 1, i.e.,

$$A_j F(m_{1j}, m_{2j}, m_{3j}, k) = A_j \left\{ m_{1j}^{\lambda_1} A_{l,1} + \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k\right)^{\frac{\lambda_2}{\gamma}} + m_{3j}^{\lambda_3} A_{l,3} \right\} \tag{A.48}$$

Then, considering the elasticity of substitution between mid-skill occupations and ICT, we obtain:

$$\sigma_{2,k} = \frac{1}{1-\gamma}$$

while the elasticity of substitution between low-skill occupations and high-skill occupations is given by:

$$\sigma_{1,3} = \frac{A_{l,1}\,\lambda_1\,{m_{1j}}^{\lambda_1} + A_{l,3}\,\lambda_3\,{m_{3j}}^{\lambda_3}}{(1-\lambda_3)A_{l,1}\,\lambda_1\,{m_{1j}}^{\lambda_1} + (1-\lambda_1)A_{l,3}\,\lambda_3\,{m_{3j}}^{\lambda_3}}$$

Then, let's define the middle composite $X_j = \left(m_{2j}^{\gamma} A_{l,2} + k_j^{\gamma} A_k\right)^{\frac{1}{\gamma}}$. In this case, the elasticity of substitution between occupation 1 and the composite is given by:

$$\sigma_{1,X} = \frac{\lambda_2 X_j^{\lambda_2} + \lambda_1 A_{l,1} m_{1j}^{\lambda_1}}{\lambda_2(1-\lambda_1) X_j^{\lambda_2} + \lambda_1(1-\lambda_2) A_{l,1} m_{1j}^{\lambda_1}}$$

Similarly, the elasticity of substitution between occupation 3 and the composite is given by:

$$\sigma_{3,X} = \frac{\lambda_2 X_j^{\lambda_2} + \lambda_3 A_{l,3} m_{3j}^{\lambda_3}}{\lambda_2(1-\lambda_3) X_j^{\lambda_2} + \lambda_3(1-\lambda_2) A_{l,3} m_{3j}^{\lambda_3}}$$

Then, if $\lambda_1 = \lambda_2 = \lambda_3 \equiv \lambda$, we have that:

$$\sigma_{1,3} = \sigma_{1,X} = \sigma_{3,X} = \frac{1}{1-\lambda}$$

■

G Estimation: Additional Derivations and Supporting Information

G.1 Additional Derivations

The following derivations use the fact that integrals involving the Fréchet distribution often have a closed-form solution, so we can calculate expectations analytically. In the model workers choose first location and then occupation. Therefore, we need to calculate the expected value of a location for a worker of a given type, without knowing yet the realization of the occupation-specific value. Here $f(t_i)$ is the pdf and $F(t_i)$ the cdf of the Fréchet distribution with shape parameter η and scale parameter 1.

$$\mathbb{E}_{\mathbf{t}}[\max_i \bar{u}(i,j,\mathbf{s})t_i] = \int \cdots \int \max\{\bar{u}(1,j,\mathbf{s})t_1, \ldots, \bar{u}(I,j,\mathbf{s})t_I\} \prod_i f(t_i) dt_1 \ldots dt_I \tag{A.49}$$

$$= \sum_i \int \bar{u}(i,j,\mathbf{s})t_i f(t_i) \prod_{i' \neq i} F\left(\frac{\bar{u}(i,j,\mathbf{s})t_i}{\bar{u}(i',j,\mathbf{s})}\right) dt_i \tag{A.50}$$

$$= \left(\sum_i \bar{u}(i,j,\mathbf{s})^{\eta}\right)^{\frac{1}{\eta}} \Gamma(1 - \frac{1}{\eta}) \tag{A.51}$$

The second line follows from the decision rule that a worker chooses occupation i if $\bar{u}(i,j,\mathbf{s})t_i > \bar{u}(i',j,\mathbf{s})t_{i'}\ \forall i'$ and that the draws of $t_i \forall i$ are i.i.d. from a Fréchet distribution. Thus, the probability of choosing i given t_i is $\prod_{i' \neq i} F\left(\frac{\bar{u}(i,j,\mathbf{s})t_i}{\bar{u}(i',j,\mathbf{s})}\right)$. The third line uses the definition of the Fréchet distribution, which allows us to calculate the analytical solution of the integral.

The choice probabilities in equations (11) and (12) follow from standard results and use the fact that draws of a_j and t_i are i.i.d. from given Fréchet distributions', see, e.g., Eaton and Kortum (2002).

G.2 Standard Errors

The estimator $\hat{\theta}$ solves

$$min_{\theta} \left(\bar{m} - m(\theta)\right)' \Omega \left(\bar{m} - m(\theta)\right).$$

where Ω is the weight matrix. In standard estimation problems the efficient choice for Ω would be to set it to the inverse of the covariance matrix of the data moment vector $\bar{m}$. However, we do not have an estimate for the full covariance matrix. Instead, we fix Ω to be diagonal with the weights

- 100 for city wage, city size, house prices, wage by occupation

- 1000 for occupation shares, IT share, standard deviation of wages by occupation, elasticity of employment share with respect to IT prices.

The estimator of the variance covariance matrix of the estimated parameters $\hat{\theta}$ is

$$\hat{V} = (\hat{M}'\Omega\hat{M})^{-1}\hat{M}'\Omega\hat{\Sigma}\Omega\hat{M}(\hat{M}'\Omega\hat{M})^{-1} \tag{A.52}$$

where $\hat{\Sigma}$ is the variance covariance matrix of the moments m_i. $\hat{M}$ is the jacobian of the moments with respect to the parameters. The jacobian is calculated numerically by finite differences.

The variances of several moments (and their covariances with the remaining moments) are not defined as we take those estimates from other sources. Further, we calibrate some parameters independently. The calculation of standard errors of the estimated parameters is done within the subset of parameters that are identified from moments for which we have estimates of the full covariance matrix. In other words, the standard errors are conditional on the remaining parameters being calibrated at their current value.

The subset of parameters for which we do not calculate the standard errors is: the elasticity of substitution between IT and labor and productivity of IT.

G.3 Preparation of Data on IT Usage

Using O*NET version 22 we calculate the employment weighted average PC Importance by occupation group as a measure of IT usage. The importance scale in O*NET starts at 1, so we subtract one from the raw measure before calculating the employment weighted average. Then we normalize the measure by its sum over the four occupation groups.

The data on the overall IT usage in the economy are constructed following Eden and Gaggl (2018).

G.4 The Elasticity of Substitution between IT and Labor

We target the elasticity of substitution between IT and labor in vom Lehn (2020). This measure was calibrated using time-series variation. Here we show the necessary derivations for calculating this elasticity of substitution in vom Lehn (2020) and our model.

G.4.1 The elasticity of substitution between IT and labor in vom Lehn (2020)

The representative firm production function is:

$$Y_t = \left[\mu_m N_{mt}^{\frac{\gamma_m-1}{\gamma_m}} + (1-\mu_m)\left[\mu_a N_{at}^{\frac{\gamma_a-1}{\gamma_a}} + (1-\mu_a)\left[(1-\mu_r)K_t^{\frac{\gamma_r-1}{\gamma_r}} + \mu_r N_{rt}^{\frac{\gamma_r-1}{\gamma_r}}\right]^{\frac{\gamma_r(\gamma_a-1)}{(\gamma_r-1)\gamma_a}}\right]^{\frac{\gamma_a(\gamma_m-1)}{(\gamma_a-1)\gamma_m}}\right]^{\frac{\gamma_m}{\gamma_m-1}} \tag{A.53}$$

Then, the firm's problem is given by:

$$\max_{K_t,N_{mt},N_{rt},N_{at}} \pi_t = Y_t - r_t K_t - w_{mt}N_{mt} - w_{rt}N_{rt} - w_{at}N_{at} \tag{A.54}$$

Then, the first order conditions are:

$$(N_{mt}): \quad \left(\frac{\gamma_m}{\gamma_m-1}\right)[\cdot]^{\frac{\gamma_m}{\gamma_m-1}-1} \times \mu_m N_{mt}^{\frac{\gamma_m-1}{\gamma_m}-1} \times \left(\frac{\gamma_m-1}{\gamma_m}\right) - w_{mt} = 0$$

Notice that: $\frac{\gamma_m}{\gamma_m-1} - 1 = \frac{\gamma_m-\gamma_m+1}{\gamma_m-1} = \frac{1}{\gamma_m-1}$ and $\frac{\gamma_m}{\gamma_m-1} \times \frac{1}{\gamma_m} = \frac{1}{\gamma_m-1}$. Therefore:

$$[\cdot]^{\frac{\gamma_m}{\gamma_m-1}-1} = Y_t^{\frac{1}{\gamma_m}}$$

while $\frac{\gamma_m-1}{\gamma_m} - 1 = \frac{\gamma_m-1-\gamma_m}{\gamma_m} = -\frac{1}{\gamma_m}$. Therefore, we have:

$$(N_{mt}): \quad w_{mt} = \mu_m \left(\frac{Y_t}{N_{mt}}\right)^{\frac{1}{\gamma_m}} \tag{FOC$_m$}$$

Before continuing, to simplify notation, define:

$$R_t = \left[(1-\mu_r)K_t^{\frac{\gamma_r-1}{\gamma_r}} + \mu_r N_{rt}^{\frac{\gamma_r-1}{\gamma_r}}\right]^{\frac{\gamma_r}{\gamma_r-1}}$$

and

$$\Omega_t = \left[\mu_a N_{at}^{\frac{\gamma_a-1}{\gamma_a}} + (1-\mu_a)R_t^{\frac{\gamma_a-1}{\gamma_a}}\right]^{\frac{\gamma_a}{\gamma_a-1}}$$

Then the F.O.C. w.r.t. N_{rt} becomes:

$$(N_{rt}): \quad \left\{ \begin{array}{l} \left(\frac{\gamma_m}{\gamma_m-1}\right)[\cdot]^{\frac{\gamma_m}{\gamma_m-1}-1} \times (1-\mu_m)\left(\frac{\gamma_a(\gamma_m-1)}{(\gamma_a-1)\gamma_m}\right)\left[\mu_a N_{at}^{\frac{\gamma_a-1}{\gamma_a}} + (1-\mu_a)R_t^{\frac{\gamma_a-1}{\gamma_a}}\right]^{\frac{\gamma_a(\gamma_m-1)}{(\gamma_a-1)\gamma_m}-1} \\ \times(1-\mu_a)\left(\frac{\gamma_r(\gamma_a-1)}{(\gamma_r-1)\gamma_a}\right)\left[(1-\mu_r)K_t^{\frac{\gamma_r-1}{\gamma_r}} + \mu_r N_{rt}^{\frac{\gamma_r-1}{\gamma_r}}\right]^{\frac{\gamma_r(\gamma_a-1)}{(\gamma_r-1)\gamma_a}-1} \mu_r\left(\frac{\gamma_r-1}{\gamma_r}\right)N_{rt}^{\frac{\gamma_r-1}{\gamma_r}-1} \end{array} \right\} - w_{rt} = 0$$

Simplifying it, we have:

$$(N_{rt}): \quad \left\{ \begin{array}{l} Y_t^{\frac{1}{\gamma_m}} \times (1-\mu_m)\left[\mu_a N_{at}^{\frac{\gamma_a-1}{\gamma_a}} + (1-\mu_a)R_t^{\frac{\gamma_a-1}{\gamma_a}}\right]^{\frac{\gamma_a(\gamma_m-1)}{(\gamma_a-1)\gamma_m}-1} \\ \times(1-\mu_a)\left[(1-\mu_r)K_t^{\frac{\gamma_r-1}{\gamma_r}} + \mu_r N_{rt}^{\frac{\gamma_r-1}{\gamma_r}}\right]^{\frac{\gamma_r(\gamma_a-1)}{(\gamma_r-1)\gamma_a}-1} \mu_r N_{rt}^{\frac{\gamma_r-1}{\gamma_r}-1} \end{array} \right\} - w_{rt} = 0$$

Then, notice that $\frac{\gamma_a(\gamma_m-1)}{\gamma_m(\gamma_a-1)} - 1 = \frac{\gamma_m-\gamma_a}{(\gamma_a-1)\gamma_m}$. In order to simplify the notation, we would like to find an exponent z such that:

$$\frac{\gamma_a}{\gamma_a-1}z = \frac{\gamma_m-\gamma_a}{(\gamma_a-1)\gamma_m} \Rightarrow z = \frac{\gamma_m-\gamma_a}{\gamma_a\gamma_m} = \frac{1}{\gamma_a} - \frac{1}{\gamma_m}$$

Similarly $\frac{\gamma_r(\gamma_a-1)}{(\gamma_r-1)\gamma_a}-1=\frac{\gamma_r\gamma_a-\gamma_r-\gamma_r\gamma_a+\gamma_a}{(\gamma_r-1)\gamma_a}=\frac{\gamma_a-\gamma_r}{(\gamma_r-1)\gamma_a}$. Again, in order to simplify the notation, we would like to find z_1 such that:

$$\frac{\gamma_r}{\gamma_r-1}z_1=\frac{\gamma_a-\gamma_r}{(\gamma_r-1)\gamma_a}\Rightarrow z_1=\frac{1}{\gamma_r}-\frac{1}{\gamma_a}$$

Then, the F.O.C. (N_{rt}) becomes:

$$(N_{rt}):\quad\left\{\begin{array}{c} Y_t^{\frac{1}{\gamma_m}}\times(1-\mu_m)\Omega_t^{\frac{1}{\gamma_a}-\frac{1}{\gamma_m}} \\ \times(1-\mu_a)R_t^{\frac{1}{\gamma_r}-\frac{1}{\gamma_a}}\mu_r N_{rt}^{-\frac{1}{\gamma_r}}\end{array}\right\}-w_{rt}=0$$

Rearranging it:

$$(N_{rt}):\quad w_{rt}=(1-\mu_m)(1-\mu_a)\mu_r\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}}\left(\frac{R_t}{N_{rt}}\right)^{\frac{1}{\gamma_r}} \qquad (\text{FOC}_r)$$

Now, the F.O.C. w.r.t. N_{at} is:

$$(N_{at}):\left\{\begin{array}{c}\left(\frac{\gamma_m}{\gamma_m-1}\right)[\cdot]^{\frac{\gamma_m}{\gamma_m-1}-1}\times(1-\mu_m)\left(\frac{\gamma_a(\gamma_m-1)}{(\gamma_a-1)\gamma_m}\right)\left[\mu_a N_{at}^{\frac{\gamma_a-1}{\gamma_a}}+(1-\mu_a)R_t^{\frac{\gamma_a-1}{\gamma_a}}\right]^{\frac{\gamma_a(\gamma_m-1)}{(\gamma_a-1)\gamma_m}-1} \\ \times\mu_a\left(\frac{\gamma_a-1}{\gamma_a}\right)N_{at}^{\frac{\gamma_a-1}{\gamma_a}-1}\end{array}\right\}-w_{at}=0$$

Simplifying it:

$$(N_{at}):\left\{\ Y_t^{\frac{1}{\gamma_m}}\times(1-\mu_m)\Omega_t^{\frac{1}{\gamma_a}-\frac{1}{\gamma_m}}\times\mu_a N_{at}^{-\frac{1}{\gamma_a}}\ \right\}-w_{at}=0$$

i.e.:

$$(N_{at}):w_{at}=(1-\mu_m)\mu_a\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{N_{at}}\right)^{\frac{1}{\gamma_a}} \qquad (\text{FOC}_a)$$

Finally, the F.O.C. w.r.t. K_t is quite similar to the one for N_{rt}. Therefore, the F.O.C. is given by:

$$(K_t):\quad r_t=(1-\mu_m)(1-\mu_a)(1-\mu_r)\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}}\left(\frac{R_t}{K_t}\right)^{\frac{1}{\gamma_r}} \qquad (\text{FOC}_K)$$

Then, putting together all the F.O.C.s, we have:

$$\left\{\begin{array}{lll} w_{mt}= & \mu_m\left(\frac{Y_t}{N_{mt}}\right)^{\frac{1}{\gamma_m}} & (\text{FOC}_m) \\ w_{rt}= & (1-\mu_m)(1-\mu_a)\mu_r\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}}\left(\frac{R_t}{N_{rt}}\right)^{\frac{1}{\gamma_r}} & (\text{FOC}_r) \\ w_{at}= & (1-\mu_m)\mu_a\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{N_{at}}\right)^{\frac{1}{\gamma_a}} & (\text{FOC}_a) \\ r_t= & (1-\mu_m)(1-\mu_a)(1-\mu_r)\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}}\left(\frac{R_t}{K_t}\right)^{\frac{1}{\gamma_r}} & (\text{FOC}_K)\end{array}\right.$$

where:

$$R_t = \left[(1-\mu_r)K_t^{\frac{\gamma_r-1}{\gamma_r}} + \mu_r N_{rt}^{\frac{\gamma_r-1}{\gamma_r}}\right]^{\frac{\gamma_r}{\gamma_r-1}}$$

and

$$\Omega_t = \left[\mu_a N_{at}^{\frac{\gamma_a-1}{\gamma_a}} + (1-\mu_a)R_t^{\frac{\gamma_a-1}{\gamma_a}}\right]^{\frac{\gamma_a}{\gamma_a-1}}$$

Before we continue, let's define the share of labor demand for occupation j as:

$$s_{jt} \equiv \frac{N_{jt}}{N_{at}+N_{rt}+N_{mt}}$$

Then, dividing the top and the bottom by N_{jt}, s_{jt} can be rewritten as:

$$s_{jt} \equiv \frac{1}{\frac{N_{at}}{N_{jt}}+\frac{N_{rt}}{N_{jt}}+\frac{N_{mt}}{N_{jt}}}$$

Proposition 3 *The elasticities of the share of workers demanded in each occupation with respect to the rental rate of capital,* $\frac{\partial s_{jt}}{\partial r_t}\frac{r_t}{s_{jt}}$ *are given by:*

$$\begin{aligned}
\frac{\frac{\partial s_{at}}{\partial r_t}}{r_t} &= \xi_{kt}[s_{rt}(\gamma_a-\gamma_r)+\xi_{rt}s_{mt}(\gamma_a-\gamma_m)] \\
\frac{\frac{\partial s_{rt}}{\partial r_t}}{r_t} &= \xi_{kt}[(1-s_{rt})(\gamma_r-\gamma_a)+\xi_{rt}s_{mt}(\gamma_a-\gamma_m)] \\
\frac{\frac{\partial s_{mt}}{\partial r_t}}{r_t} &= \xi_{kt}[s_{rt}(\gamma_a-\gamma_r)+\xi_{rt}(1-s_{mt})(\gamma_m-\gamma_a)]
\end{aligned}$$

where ξ_{kt} *is the share of all routine income paid to capital, i.e.:*

$$\xi_{kt} = \frac{r_tK_t}{r_tK_t+w_{rt}N_{rt}}$$

and ξ_{rt} *is the share of income paid to routine tasks in the CES nest combining abstract and routine tasks, i.e.:*

$$\xi_{kt} = \frac{r_tK_t+w_{rt}N_{rt}}{r_tK_t+w_{rt}N_{rt}+w_{at}N_{at}}$$

Given these conditions, a decline in the rental rate of capital will generate an increase in the share of labor demand from abstract jobs if $\gamma_r-\gamma_a > \frac{\xi_{rt}s_{mt}}{s_{rt}}(\gamma_a-\gamma_m)$ *and a decrease in the share of labor demand from routine jobs if* $\gamma_r-\gamma_a > \frac{\xi_{rt}s_{mt}}{1-s_{rt}}(\gamma_m-\gamma_a)$.

Proof. First of all, from the FOCs (FOC_a) and (FOC_r), we have:

$$\frac{w_{at}}{w_{rt}} = \frac{(1-\mu_m)\mu_a\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{N_{at}}\right)^{\frac{1}{\gamma_a}}}{(1-\mu_m)(1-\mu_a)\mu_r\left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}}\left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}}\left(\frac{R_t}{N_{rt}}\right)^{\frac{1}{\gamma_r}}}$$

Simplifying it, we have:

$$\frac{w_{at}}{w_{rt}} = \left(\frac{\mu_a}{1-\mu_a}\right) \mu_r^{-1} \left(\frac{R_t}{N_{at}}\right)^{\frac{1}{\gamma_a}} \left(\frac{N_{rt}}{R_t}\right)^{\frac{1}{\gamma_r}} \tag{A.55}$$

while FOCs (FOC_r) and (FOC_K) give us:

$$\frac{w_{rt}}{r_t} = \frac{(1-\mu_m)(1-\mu_a)\mu_r \left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}} \left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}} \left(\frac{R_t}{N_{rt}}\right)^{\frac{1}{\gamma_r}}}{(1-\mu_m)(1-\mu_a)(1-\mu_r) \left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}} \left(\frac{\Omega_t}{R_t}\right)^{\frac{1}{\gamma_a}} \left(\frac{R_t}{K_t}\right)^{\frac{1}{\gamma_r}}}$$

Simplifying

$$\frac{w_{rt}}{r_t} = \left(\frac{\mu_r}{1-\mu_r}\right) \left(\frac{K_t}{N_{rt}}\right)^{\frac{1}{\gamma_r}}$$

Rearranging:

$$K_t = \left(\frac{w_{rt}}{r_t}\right)^{\gamma_r} \left(\frac{1-\mu_r}{\mu_r}\right)^{\gamma_r} N_{rt}$$

Substituting it back into the expression for R_t, we have:

$$R_t = \left\{\left[(1-\mu_r)^{\gamma_r} (r_t)^{1-\gamma_r} + \mu_r^{\gamma_r} (w_{rt})^{1-\gamma_r}\right]\right\}^{\frac{\gamma_r}{\gamma_r - 1}} \left(\frac{w_{rt}}{\mu_r}\right)^{\gamma_r} N_{rt}$$

Rearranging:

$$\frac{N_{rt}}{R_t} = \left[(1-\mu_r)^{\gamma_r} (r_t)^{1-\gamma_r} + \mu_r^{\gamma_r} (w_{rt})^{1-\gamma_r}\right]^{\frac{\gamma_r}{1-\gamma_r}} \left(\frac{\mu_r}{w_{rt}}\right)^{\gamma_r}$$

Then, define:

$$C_{R,t} = \left[(1-\mu_r)^{\gamma_r} (r_t)^{1-\gamma_r} + \mu_r^{\gamma_r} (w_{rt})^{1-\gamma_r}\right]^{\frac{1}{1-\gamma_r}}$$

Substituting it back, we have:

$$\left(\frac{N_{rt}}{R_t}\right)^{\frac{1}{\gamma_r}} = \left(\frac{\mu_r C_{R,t}}{w_{rt}}\right) \tag{A.56}$$

Similarly, we have that:

$$\left(\frac{R_t}{N_{rt}}\right)^{\frac{1}{\gamma_a}} = \left(\frac{w_{rt}}{\mu_r C_{R,t}}\right)^{\frac{\gamma_r}{\gamma_a}}$$

rearranging:

$$\left(\frac{R_t}{N_{at}}\right)^{\frac{1}{\gamma_a}} = \left(\frac{w_{rt}}{\mu_r C_{R,t}}\right)^{\frac{\gamma_r}{\gamma_a}} \times \left(\frac{N_{rt}}{N_{at}}\right)^{\frac{1}{\gamma_a}}$$

Substituting it back into equation (A.55), we have:

$$\frac{w_{at}}{w_{rt}} = \left(\frac{\mu_a}{1-\mu_a}\right) \mu_r^{-1} \left(\frac{w_{rt}}{\mu_r C_{R,t}}\right)^{\frac{\gamma_r}{\gamma_a}} \left(\frac{\mu_r C_{R,t}}{w_{rt}}\right) \left(\frac{N_{rt}}{N_{at}}\right)^{\frac{1}{\gamma_a}} \tag{A.57}$$

simplifying it:

$$\left(\frac{N_{at}}{N_{rt}}\right)^{\frac{1}{\gamma_a}} = \left(\frac{\mu_a}{1-\mu_a}\right)^{\gamma_a} \mu_r^{-\gamma_r} \left(\frac{w_{rt}}{C_{R,t}}\right)^{\gamma_r} \left(\frac{C_{R,t}}{w_{at}}\right)^{\gamma_a} \tag{A.58}$$

Similarly, from (FOC$_a$)/(FOC$_m$), we have:

$$\frac{w_{at}}{w_{mt}} = \frac{(1-\mu_m)\mu_a \left(\frac{Y_t}{\Omega_t}\right)^{\frac{1}{\gamma_m}} \left(\frac{\Omega_t}{N_{at}}\right)^{\frac{1}{\gamma_a}}}{\mu_m \left(\frac{Y_t}{N_{mt}}\right)^{\frac{1}{\gamma_m}}}$$

Rearranging it:

$$\frac{w_{at}}{w_{mt}} = \left(\frac{1-\mu_m}{\mu_m}\right)\mu_a \frac{\left(\frac{\Omega_t}{N_{at}}\right)^{\frac{1}{\gamma_a}}}{\left(\frac{\Omega_t}{N_{mt}}\right)^{\frac{1}{\gamma_m}}}$$

$$\Omega_t = \left[\mu_a + (1-\mu_a)\left(\frac{R_t}{N_{at}}\right)^{\frac{\gamma_a-1}{\gamma_a}}\right]^{\frac{\gamma_a}{\gamma_a-1}} N_{at}$$

Since from equations (A.55) and (A.56), we have:

$$\begin{aligned}\left(\frac{R_t}{N_{at}}\right)^{\frac{\gamma_a-1}{\gamma_a}} &= \left(\frac{1-\mu_a}{\mu_a}\right)^{\gamma_a-1} \left(\frac{w_{at}}{C_{Rt}}\right)^{\gamma_a-1} \\ &= \left(\frac{1-\mu_a}{\mu_a}\right)^{\gamma_a-1} \left(\frac{C_{Rt}}{w_{at}}\right)^{1-\gamma_a}\end{aligned}$$

Substituting it back, we have:

$$\Omega_t = \left[\mu_a + (1-\mu_a)\left(\frac{1-\mu_a}{\mu_a}\right)^{\gamma_a-1} \left(\frac{C_{Rt}}{w_{at}}\right)^{1-\gamma_a}\right]^{\frac{\gamma_a}{\gamma_a-1}} N_{at}$$

Rearranging it:

$$\Omega_t = \left[\frac{\mu_a^{\gamma_a} w_{at}^{1-\gamma_a} + (1-\mu_a)^{\gamma_a} C_{Rt}^{1-\gamma_a}}{\mu_a^{\gamma_a-1} w_{at}^{1-\gamma_a}}\right]^{\frac{\gamma_a}{\gamma_a-1}} N_{at}$$

i.e.:

$$\frac{\Omega_t}{N_{at}} = \left[\mu_a^{\gamma_a} w_{at}^{1-\gamma_a} + (1-\mu_a)^{\gamma_a} C_{Rt}^{1-\gamma_a}\right]^{\frac{\gamma_a}{\gamma_a-1}} \left(\frac{w_{at}}{\mu_a}\right)^{\gamma_a}$$

Define:

$$C_{\Omega,t} \equiv \left[\mu_a^{\gamma_a} w_{at}^{1-\gamma_a} + (1-\mu_a)^{\gamma_a} C_{Rt}^{1-\gamma_a}\right]^{\frac{\gamma_a}{\gamma_a-1}}$$

Then:

$$\frac{\Omega_t}{N_{at}} = C_{\Omega,t}\left(\frac{w_{at}}{\mu_a}\right)^{\gamma_a}$$

and

$$\frac{\Omega_t}{N_{mt}} = C_{\Omega,t}\left(\frac{w_{at}}{\mu_a}\right)^{\gamma_a} \frac{N_{at}}{N_{mt}}$$

Substituting it back into the expression for $\frac{w_{at}}{w_{mt}}$, we have:

$$\frac{w_{at}}{w_{mt}} = \left(\frac{1-\mu_m}{\mu_m}\right)\mu_a \frac{\left(C_{\Omega,t}\left(\frac{w_{at}}{\mu_a}\right)^{\gamma_a}\right)^{\frac{1}{\gamma_a}}}{\left(C_{\Omega,t}\left(\frac{w_{at}}{\mu_a}\right)^{\gamma_a}\frac{N_{at}}{N_{mt}}\right)^{\frac{1}{\gamma_m}}}$$

■

G.4.2 Elasticities in our model

The labor demand and capital demand in our model are given by (15) and (16). For simplicity, call the solution to (15) and (16): $m_{ij}(\mathbf{w}, \mathbf{r})$ and $k_{ij}(\mathbf{w}, \mathbf{r})$. Given capital demand and prices we calculate the elasticity of the share of labor demanded in an occupation. To target the elasticities given in vom Lehn (2020) we sum together routine manual and routine cognitive jobs when calculating the elasticity. Finally, we target the elasticity of labor demand in the overall economy, that is we aggregate over all cities j.

G.5 Additional Moments and Parameter Estimates

In Table A-31 we present the city level moments, that we targeted in the estimation, but omitted from the main text. Moments are almost perfectly fit, as we allowed for city specific productivity and housing supply shifters. The corresponding parameter estimates are shown in Table A-32. The estimates reflect the heterogeneity across cities in employment, house prices and occupational specialization.

Moment	**City 1**	**City 2**	**City 3**	**City 4**	**City 5**	**City 6**	**City 7**	**City 8**	**City 9**	**City 10**	**City 11**	**City 12**	**City 13**	**City 14**	**City 15**	**City 16**	**City 17**	**City 18**
Average log wage																		
Model	6.6	6.7	6.7	6.7	6.7	6.7	6.7	6.8	6.8	6.9	6.9	7.0	7.0	6.8	7.0	6.9	6.8	7.1
Data	6.6	6.7	6.7	6.7	6.7	6.7	6.7	6.8	6.8	6.9	6.9	7.0	7.0	6.8	7.0	6.9	6.8	7.1
Log rent (index)																		
Model	-0.43	-0.35	-0.19	-0.24	-0.26	-0.18	-0.22	-0.092	-0.098	0.044	0.061	0.12	0.2	0.12	0.33	0.47	0.4	0.54
Data	-0.43	-0.35	-0.19	-0.25	-0.26	-0.18	-0.22	-0.094	-0.098	0.044	0.061	0.12	0.2	0.12	0.33	0.47	0.4	0.54
Log size diff																		
Model	-2.3	-1.9	-0.92	-1.7	-1.7	-1.2	-1.8	-2.1	-0.081	-0.42	0.22	-0.51	-0.15	-0.21	0.91	-0.89	0.87	
Data	-2.3	-1.9	-0.92	-1.7	-1.7	-1.2	-1.8	-2.1	-0.081	-0.42	0.22	-0.51	-0.15	-0.21	0.91	-0.9	0.87	
Occupation Share diff																		
non-routine manual																		
Model		-0.0011	-0.01	-0.01	-0.014	-0.0067	-0.0034	-0.0091	-0.019	-0.0081	-0.011	-0.015	-0.011	0.00076	0.023	0.012	0.0054	-0.00066
Data		-0.0014	-0.0085	-0.01	-0.014	-0.0039	-0.0027	-0.0089	-0.018	-0.0058	-0.01	-0.011	-0.0095	0.0017	0.027	0.014	0.0063	0.00019
routine manual																		
Model		-0.024	-0.059	-0.031	-0.025	-0.061	-0.037	-0.035	-0.046	-0.082	-0.06	-0.1	-0.1	-0.057	-0.099	-0.09	-0.041	-0.11
Data		-0.026	-0.068	-0.033	-0.026	-0.073	-0.04	-0.036	-0.049	-0.092	-0.067	-0.12	-0.11	-0.061	-0.12	-0.1	-0.045	-0.11
routine cognitive																		
Model		0.0031	-0.00074	-0.006	-0.0097	0.001	-0.0083	-0.0053	-0.014	-0.021	-0.0099	-0.026	-0.03	-0.016	-0.026	-0.025	-0.0067	-0.04
Data		0.0058	0.0054	-0.004	-0.0085	0.0084	-0.006	-0.0035	-0.012	-0.014	-0.005	-0.016	-0.025	-0.013	-0.014	-0.019	-0.0038	-0.042
non-routine cognitive																		
Model		0.022	0.07	0.047	0.049	0.067	0.049	0.049	0.079	0.11	0.081	0.14	0.14	0.072	0.1	0.1	0.042	0.15
Data		0.021	0.072	0.047	0.048	0.069	0.049	0.049	0.079	0.11	0.082	0.14	0.14	0.073	0.11	0.11	0.043	0.16

Table A-31: City level Moments

Parameter	City 1	City 2	City 3	City 4	City 5	City 6	City 7	City 8	City 9	City 10	City 11	City 12	City 13	City 14	City 15	City 16	City 17	City 18
TFP A_j	58000.0	60000.0	77000.0	80000.0	87000.0	73000.0	83000.0	79000.0	110000.0	130000.0	98000.0	170000.0	190000.0	110000.0	140000.0	140000.0	79000.0	240000.0
Amenity a_j	1.0	1.1	1.4	1.1	1.1	1.3	1.1	1.0	1.6	1.5	1.8	1.4	1.6	1.7	2.1	1.5	2.4	1.6
House price shifter ϕ_j	0.098	0.052	0.067	0.037	0.062	0.024	0.032	0.05	0.019	0.012	0.0011	0.0051	0.011	0.0027	0.00035	0.00044	4.7e-5	0.00038
House price elasticity ϵ_j	0.39	0.5	0.41	0.56	0.46	0.6	0.6	0.59	0.55	0.68	0.96	0.83	0.69	0.91	1.1	1.4	1.4	1.3
Occupation Productivity $A_{l,ij}$																		
non-routine manual	1.7	1.7	1.8	1.8	1.8	1.8	1.7	1.8	1.9	1.7	1.8	1.7	1.7	1.6	1.3	1.4	1.6	1.5
routine manual	1.4	2.0	2.9	1.9	1.7	3.0	2.0	2.0	2.1	3.1	2.7	4.0	3.7	2.4	3.9	3.3	2.2	4.1
routine cognitive	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
non-routine cognitive	1.1	1.2	1.3	1.2	1.3	1.3	1.3	1.2	1.3	1.4	1.3	1.5	1.5	1.3	1.4	1.4	1.2	1.6

Table A-32: City level Parameters

G.6 Alternative Calibrations

In this section, we compare the results of the counterfactual with respect to IT prices under a variety of alternative specifications for the externally calibrated parameters. The main results in the paper are presented for 18 city bins, here we present the results with just 3 city bins to save computational cost. For each alternative calibration, we re-estimate the parameters to fit the same moments and then perform the IT price counterfactual. We report here the change in the employment share of routine cognitive employment in the most expensive cities minus the change in the cheapest cities, i.e. the change in sorting of routine cognitive jobs, in response to a change in IT prices. For simplicity, we report results as relative to the baseline with all external parameter values set to the baseline values reported in the paper.

We consider the following additional specifications:

1. Dispersion of idiosyncratic tastes for cities τ for alternative values in range 2 to 8, see Table A-33;

2. Dispersion of idiosyncratic tastes for occupations η for alternative values in range 2 to 8, see Table A-33;

3. Elasticity of substitution between occupations is $\frac{1}{1-\lambda}$, alternative values in range: -0.75 to 0.5, see Table A-34;

4. Housing supply elasticity set to economy-wide average instead of city-specific supply elasticity, see Table A-35;

5. Elasticity of employment share with respect to IT prices target set to 2000s values (instead of 1990s), see Table A-35;

6. Set the Elasticity of Substitution between IT and labor equal in manual (non-routine and routine) instead of routine cognitive and routine manual, see Table A-35.

Table A-33 shows the sorting of routine-cognitive jobs result relative to the baseline. Each row corresponds to a value of the Frechet tail parameter, the columns refer to which tail parameter was changed relative to the baseline. The column τ thus shows that a larger labour supply elasticity across cities implies a stronger sorting result. However, the magnitude of the difference is limited. In contrast, varying η governing the labour supply elasticity across occupations, has a minimal effect on the size of the sorting result. The only larger difference is for $\eta = 2$, but in that case the estimation does not fit the data very well. In short, the labour supply elasticity needs to be sufficiently large to fit the data at all and the sorting result is stronger the larger τ, which governs labour supply elasticity across cities.

Next we show how the sorting result changes with the elasticity of substitution across occupations in Table A-34. The CES production function implies an EoS of $\frac{1}{1-\lambda}$, which we set to $\lambda = -0.33$ (EoS$= 0.75$) in the baseline. Compared to the baseline a lower substitution elasticity implies

τ	Sorting result relative to baseline	η	Sorting result relative to baseline
2	80.3	2	83.9
3	95.2	3	95.0
4	100.0	4	101.3
5	106.1	5	100.0
6	109.4	6	101.2
7	113.2	7	99.9
8	114.6	8	100.3

Table A-33: Labour Supply elasticities and change in sorting of routine-cognitive employment relative to baseline (100).

stronger sorting results, while larger values below zero, imply slightly weaker results. For positive values (an EoS > 1) the results are again very similar. Thus, within a range of typical estimates, e.g. Goos et al. (2014) estimate $\lambda \approx -0.11$, there are limited differences in the main result.

λ	Sorting result relative to baseline
-0.75	150.8
-0.5	123.0
-0.33	100.0
-0.2	89.2
-0.15	90.3
-0.11	85.2
0.2	106.5
0.25	106.3
0.3	113.0
0.5	91.9

Table A-34: Occupation Substitutability and change in sorting of routine-cognitive employment relative to baseline (100).

We also provide results for following additional variations: (i) common housing supply elasticity across cities, (ii) same substitution elasticity for non-routine and routine manual, instead of routine manual and routine cognitive, (iii) target elasticities for the 2000s instead of 1990s. Table A-35 shows the results for these specifications relative to the baseline specification.

(i) Setting the housing supply elasticity equal across cities to the economy-wide average, instead of the city specific housing supply elasticity as in the baseline, we find very similar slightly larger results for the impact of IT prices on the sorting of routine cognitive jobs.

(ii) In the baseline specification we set $\gamma_{RC} = \gamma_{RM}$, that is the substitution elasticity between IT and labor is assumed to be the same in routine cognitive and routine manual jobs (close to the specification in vom Lehn (2020)). In contrast, setting the substitution elasticity equal for non-routine and routine manual instead implies a doubling of the impact of IT prices on the sorting of routine cognitive jobs. We stick to the baseline calibration as it also fits more closely with the estimates in Caunedo et al. (2023).

(iii) Lastly, targeting the elasticity for the 2000s instead of the 1990s implies a somewhat smaller impact of IT prices on the sorting of jobs.

Alternative Specification	**Sorting result relative to baseline**
common housing supply elasticity $\epsilon_j = \bar{\epsilon}$	121
Normalization $\gamma_{NRM} = \gamma_{RM}$	205
Targeted Occupation share-IT price Elasticity values for 2000s	80

Table A-35: Additional specifications and change in sorting of routine-cognitive employment relative to baseline (100).

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Online Appendix

Table of Contents

A Employment and Establishment Coverage: Comparison to NETS Data

A.1 NETS Data

The National Establishment Time Series (NETS) is an annual series consisting of establishment-level longitudinal microdata covering, in principle, the universe of US Business. The starting point for the NETS database was annual snapshots (taken every January) of the full Duns Marketing Information (DMI) file that followed over 58.8 million establishments between January 1990 and January 2020. These snapshots actually used the DMI file to determine which establishments were active in January of each year in question. The database includes information on: business name, address and contact information, headquarters ID, number of establishments per firm, industry classification, type of proprietorship, employment by location and estimated annual establishment sales. Finally, NETS includes unique firm and establishment identifiers through D&B hqduns and duns numbers.

As highlighted in Section B.1, there are some key distinctions between NETS and the databases provided by official sources such as the CBP. First, NETS information is not collected at a particular time of year, but throughout the year. Second, in NETS an establishment is defined as a "unique line of business (SIC8) at a unique location." So, it is possible to have more than one establishment at a location. Third, NETS data include not only firm owners among establishment employees, but also self-employed, contract, and temporary workers. Finally, there are some drawbacks to the data, highlighted by Barnatchez et al. (2017) and Crane and Decker (2020), in particular due to data staleness as well as issues with data imputation. While the data are reported to be regularly collected, some employment level information seems to be updated less frequently than official sources counterparts. Similarly, imputed data points differ quite significantly from their administrative data counterparts.

A.2 Comparison to Ci Aberdeen Data: IT Budget Sample

Ci Aberdeen data have lots of similarities to the NETS data. First, both are indexed by duns numbers and have imputed values for establishment sales. Second, establishment and employment data tend to follow similar definitions in both samples, including non-employment establishments. However, as we compare the two samples, we do observe some key distinctions. First, headquarter IDs are quite distinct between the two databases. Second, employment levels are quite distinct among large establishments. We present more details below.

Table OA-1: Coverage Ci Aberdeen relative to NETS

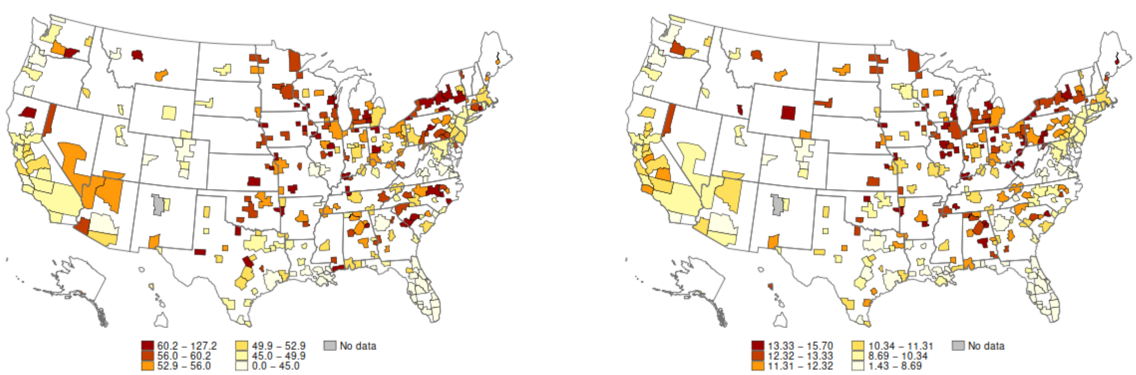
	Mean	**S.D.**	**p10**	**p25**	**p50**	**p75**	**p90**	**N**
IT Budget Sample								
Fraction Emp. in Ci	52%	12%	42%	47%	53%	59%	62%	279
Fraction Est. in Ci	11%	2%	8%	10%	11%	13%	14%	277
Fraction Sales in Ci	52%	9%	44%	49%	53%	56%	60%	279
ERP Sample								
Fraction Emp. in Ci	20%	7%	13%	16%	20%	23%	27%	279
Fraction Est. in Ci	1%	0%	1%	1%	1%	1%	1%	277
Fraction Sales in Ci	17%	6%	10%	13%	16%	20%	23%	279

Similar to the comparison to the CBP presented in Section B, while our IT budget sample covers more than 50 percent of employment in NETS, it only covers about 11% of establishment (see Table OA-1. However, the low establishment coverage is due to low coverage of small establishments. In fact, our sample covers above 50 percent of NETS establishments for establishments with 10 employees or more (see Table OA-2).

In terms of industry coverage, we see that our sample has a low coverage in leisure and hospitality, trade, transportation, and utility, as well as other services in both establishment and employment coverage (see Tables OA-3 and OA-4).

Table OA-2: Coverage Ci Aberdeen relative to NETS by establishment size

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
1 to 4 Employees	2%	1%	2%	2%	2%	3%	3%	279
5 to 9 Employees	23%	4	19%	21%	23%	25%	26%	279
10 to 19 Employees	42%	8%	35%	40%	43%	47%	49%	279
20 to 49 Employees	48%	8%	42%	46%	49%	52%	55%	279
50 to 99 Employees	53%	8%	47%	50%	54%	57%	60%	279
100 to 249 Employees	60%	11%	51%	56%	61%	66%	72%	279
250 to 499 Employees	72%	22%	50%	62%	71%	82%	95%	279
500 to 999 Employees	91%	41%	55%	70%	83%	106%	133%	279
1,000 or more Employees	142%	71%	75%	100%	125%	167%	225%	277
ERP Sample								
1 to 4 Employees	0%	0%	0%	0%	0%	0%	0%	279
5 to 9 Employees	0%	0%	0%	0%	0%	0%	0%	279
10 to 19 Employees	1%	0%	1%	1%	1%	2%	2%	279
20 to 49 Employees	5%	1%	4%	4%	5%	6%	7%	279
50 to 99 Employees	12%	4%	9%	11%	12%	14%	17%	279
100 to 249 Employees	28%	7%	20%	24%	28%	33%	38%	279
250 to 499 Employees	37%	18%	21%	28%	35%	45%	53%	279
500 to 999 Employees	57%	34%	27%	38%	49%	67%	100%	279
1,000 or more Employees	95%	59%	45%	60%	79%	110%	167%	277



(a) Employment Coverage

(b) Establishment Coverage

Figure OA-1: Geographical distribution of Ci coverage relative to NETS: IT budget sample

Finally, in terms of geographic coverage, the IT budget sample shows a higher coverage in the Midwest and East Coast regions, while coverage rates are somewhat lower in the West Coast and Western regions. Patterns are quite similar for both employment (figure OA-1a) and establishments (figure OA-1b). That said, coverage rates even in areas with low coverage are still meaningful (above 45 percent for employment and above 8 percent for establishments).

Table OA-3: Ci coverage relative to NETS: Employment by Industry

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
Manufacturing	75%	22%	53%	64%	73%	83%	97%	279
Construction	46%	11%	35%	41%	45%	52%	58%	279
Information	64%	27%	43%	52%	61%	70%	84%	279
Finance	54%	21%	36%	42%	51%	62%	76%	279
Professional & Bus Services	39%	16%	22%	29%	36%	45%	55%	279
Education and Health	75%	18%	59%	66%	75%	81%	92%	279
Leisure and Hospitality	19%	9%	11%	14%	18%	23%	29%	279
Public Adm	77%	60%	49%	59%	69%	82%	97%	279
Trade, Transp., and Util.	36%	11%	25%	30%	35%	40%	46%	279
Mining	56%	47%	10%	34%	52%	71%	94%	279
Other Services	35%	20%	21%	26%	32%	39%	48%	279
ERP Sample								
Manufacturing	35%	18%	15%	24%	32%	42%	54%	279
Construction	7%	7%	2%	4%	6%	10%	14%	279
Information	24%	17%	8%	15%	21%	30%	44%	279
Finance	14%	13%	3%	5%	11%	19%	28%	279
Professional & Bus Services	11%	12%	3%	5%	9%	14%	19%	279
Education and Health	34%	14%	21%	26%	33%	40%	47%	279
Leisure and Hospitality	7%	7%	1%	3%	5%	8%	12%	279
Public Adm	31%	39%	11%	18%	25%	33%	48%	279
Trade, Transp., and Util.	11%	9%	3%	6%	9%	13%	17%	279
Mining	11%	24%	0%	0%	0%	12%	36%	279
Other Services	9%	15%	2%	4%	7%	11%	17%	279

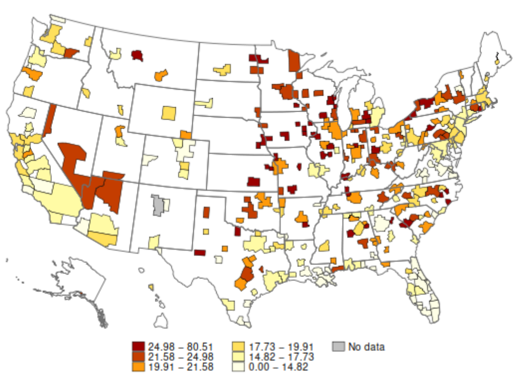
A.3 Comparison to Ci Aberdeen Data: ERP Sample

As discussed in Section 2, our ERP sample is limited. Our information on ERP adoption covers on average only 20 percent of workers and 1 percent of establishments in the MSA, compared to NETS (see table OA-1). Moreover, as presented in Table A-6, even after controlling for establishment size, MSA average coverage is above 28 percent only for establishments that have 100 employees or more. Finally, Table OA-4 shows that the ERP sample covers less than 35 percent of establishments in all industry sectors but public administration. However, since the coverage is tilted toward larger establishments, employment coverage varies from 10 (Leisure and Hospitality) to 36 percent (Manufacturing) of the NETS industry employment (Table OA-3).

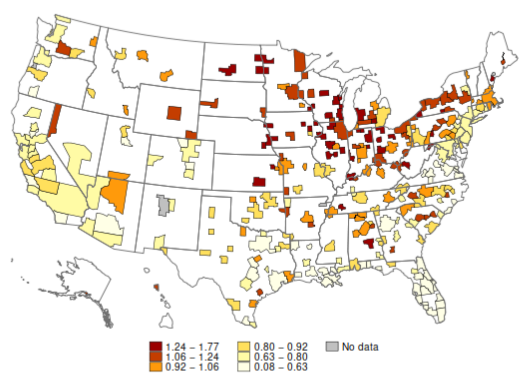
Finally, in terms of geographic coverage, the ERP sample shows a higher coverage in the Midwest and East Coast regions, while coverage rates are somewhat lower in the West Coast and Western regions. Patterns are quite similar for both employment (Figure OA-2a) and establishments (Figure OA-2b). That said, coverage rates even in areas with low coverage are still meaningful (above 15 percent for employment and above 0.6 percent for establishments).

Table OA-4: Ci coverage relative to NETS: Establishments by industry

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
Manufacturing	32%	8%	23%	27%	32%	38%	41%	279
Construction	8%	2%	5%	7%	8%	9%	11%	279
Information	23%	7%	13%	18%	22%	27%	33%	279
Finance	18%	5%	12%	15%	18%	21%	24%	279
Professional & Bus Services	5%	1%	3%	4%	5%	5%	6%	279
Education and Health	28%	6%	22%	25%	28%	31%	34%	279
Leisure and Hospitality	7%	2%	5%	6%	7%	8%	9%	279
Public Adm	59%	9%	51%	56%	61%	64%	68%	279
Trade, Transp., and Util.	8%	2%	6%	7%	8%	9%	10%	279
Mining	23%	12%	8%	15%	22%	31%	38%	279
Other Services	6%	2%	4%	5%	6%	6%	7%	279
ERP Sample								
Manufacturing	4%	2%	2%	3%	4%	6%	7%	279
Construction	0%	0%	0%	0%	0%	1%	1%	279
Information	3%	1%	1%	2%	2%	3%	5%	279
Finance	1%	0%	0%	0%	1%	1%	1%	279
Professional & Bus Services	0%	0%	0%	0%	0%	0%	1%	279
Education and Health	2%	1%	1%	2%	2%	2%	3%	279
Leisure and Hospitality	1%	0%	0%	1%	1%	1%	1%	279
Public Adm	5%	2%	3%	4%	5%	6%	8%	279
Trade, Transp., and Util.	1%	0%	0%	0%	1%	1%	1%	279
Mining	2%	3%	0%	0%	0%	3%	6%	279
Other Services	0%	0%	0%	0%	0%	1%	1%	279



(a) Employment Coverage



(b) Establishment Coverage

Figure OA-2: Geographical distribution of Ci coverage relative to NETS: ERP sample

B Measures of Skill Concentration

We now calculate measures of the concentration of skills across regions. These measures allow us to test if we have observed an increase in the spatial dispersion of skills across MSAs in the last 25 years. Moreover, these measures abstract from issues of long-run trends in the composition of the labor force. Consequently, we are able to focus on the correlation between the spatial dispersion of skills and an MSA's characteristics – in particular size and cost of housing. We consider three simple measures: the location quotient that compares the skill distribution in the MSA against the overall skill distribution in the economy, the Ellison and Glaeser (1997) index of industry concentration, and an adjusted version of this index proposed by Oyer and Schaefer (2016). The latter two indexes attempt to measure concentration by comparing it against a distribution that would be obtained by chance (the "dartboard approach").

B.1 Location Quotient

As a first pass, we consider a concentration measure that compares the distribution in a given MSA against the distribution in the overall economy. In particular, we consider that the degree of concentration of skill i in city j (λ_{ij}) is given by:

$$\lambda_{ij} = \frac{\frac{m_{ij}}{S_j}}{\frac{M_i}{\sum_{l=1}^{N} M_l}} \tag{OA.1}$$

Intuitively, if a MSA is more concentrated in skill level i than the economy at large, this index's value would be above 1. Moreover, this measure has two additional benefits. First, by focusing on shares, it reduces the impact of the MSA's overall size on the analysis. Second, by comparing the region against the economy-wide distribution, it takes into account the potential changes in the national labor market. Consequently, it allows us to focus on the increase or decrease in concentration across regions as well as how it correlates to these regions' characteristics.

Following what has been show in other sections, we consider two time periods: 1990 and 2015. Moreover, following Cortes et al. (2017), we divide the occupations in four groups: non-routine manual, routine manual, routine cognitive, and non-routine cognitive. We divide the regions into two groups around the median. We use the log rent index in 1980, i.e. cheap vs. expensive, as the measure to separate the MSAs. Results are presented in Table OA-5.

As we can see from Table OA-5, in 1990, cheaper cities had on average a higher concentration in routine manual jobs, a lower concentration in cognitive jobs (both routine and non-routine), and close to at par in non-routine manual jobs when compared to expensive cities. Differently, in 2015 we see cheap cities being on average more concentrated in routine cognitive jobs, while we see minor changes in the other occupation categories. These results are in line with what our theoretical results would predict.

Finally, Figures OA-3 and OA-4 present the density distributions of the location quotients for small and large cities across occupation groups and time. While we observe that there is significant variance in this index across MSAs, the overall message is the same as the one presented in Table OA-5.

Table OA-5: Simple measure of concentration across skill and city size groups

Panel A: 1990								
	Non-Routine Manual		*Routine Manual*		*Routine Cognitive*		*Non-Routine Cognitive*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Expensive City	1.05	1.01	1.03	1.00	0.98	0.98	0.97	0.95
Cheap City	1.06	1.06	1.26***	1.23†††	0.92***	0.91†††	0.86***	0.86†††
Panel B: 2015								
	Non-Routine Manual		*Routine Manual*		*Routine Cognitive*		*Non-Routine Cognitive*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Expensive City	1.02	0.97	1.07	1.04	0.99	1.00	0.95	0.95
Cheap City	1.03	1.02	1.25***	1.23†††	1.02*	1.03††	0.87***	0.87†††

***,**,* represent significance at 1, 5, and 10% respectively in a t-test of means with unequal variances.
†††,††, † represent significance at 1, 5, and 10% respectively in a Wilcoxon rank-sum test of medians.

B.2 Ellison-Glaeser (1997) Index

We now adapt the concentration index presented by Ellison and Glaeser (1997) for the skill distribution context. Denote λ_i as the EG concentration index for skill i. To define this index, we first introduce some notation. Define s_{ij} as the share of workers of skill i in city j, i.e., $s_{ij} = \frac{m_{ij}}{M_i}$. Let x_j be the share of total employment in city j, i.e., $x_j = \frac{S_j}{\sum_{l=1}^{N} M_l}$. Then, our measure of spatial concentration of skill i is given by:

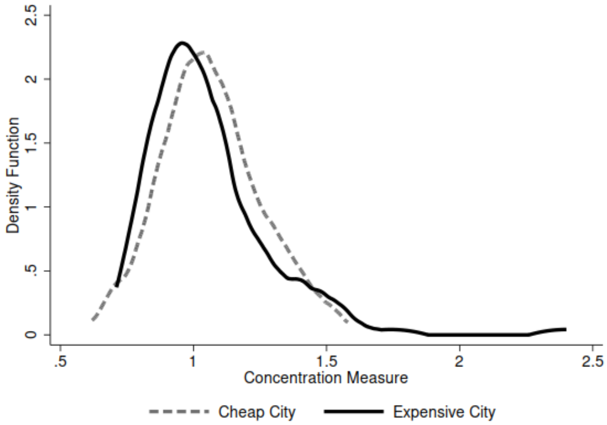
$$\lambda_i = \frac{\sum_j (s_{ij} - x_j)^2}{1 - \sum_j x_j^2} \tag{OA.2}$$

According to Ellison and Glaeser (1997), there are several advantages in using this index. First, it is easy to compute with readily available data. Second, the scale of the index allows us to make comparisons with a no-agglomeration case in which the data are generated by the simple dartboard model of random location choices (in which case $E(\lambda_i) = 0$). Finally, the index is comparable across populations of different skill sizes. Notice that in this case, we have one index per skill group per year. Consequently, we are unable to compare expensive and cheap cities. However, we are able to see if skill groups became more or less concentrated across cities over time.

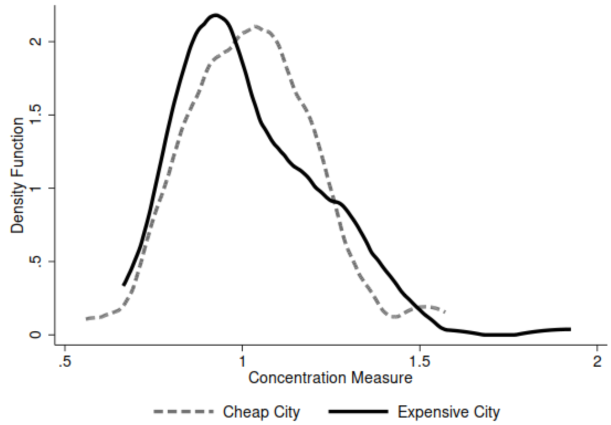
Table OA-6: Ellison-Glaeser Index

	1990	**2015**	**% Change**
Non-Routine Manual	0.00032	0.00038	18.66
Routine Manual	0.00075	0.00076	0.75
Routine Cognitive	0.00007	0.00014	108.90
Non-Routine Cognitive	0.00029	0.00030	3.38

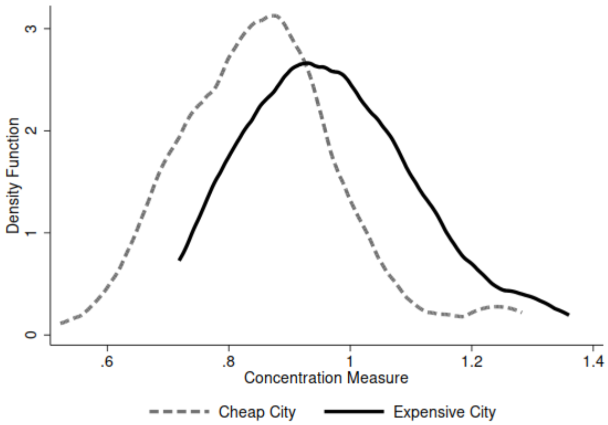
Results are presented in Table OA-6. As we can see, while routine manual occupations have



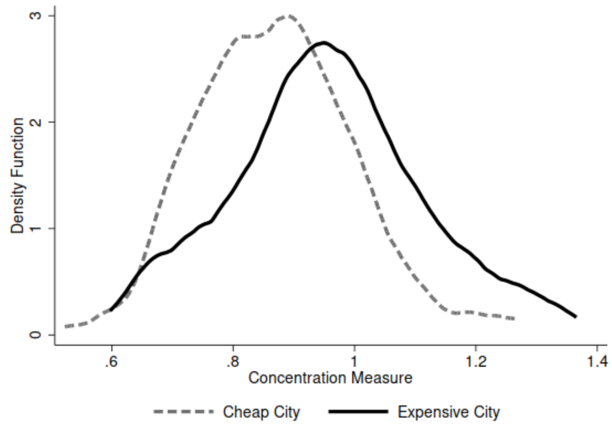
(a) Non-Routine Manual: 1990



(b) Non-Routine Manual: 2015



(c) Non-Routine Cognitive: 1990



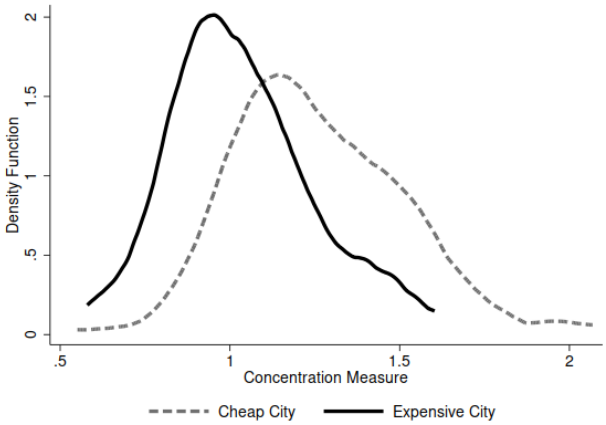
(d) Non-Routine Cognitive: 2015

Figure OA-3: Non-routine occupations LQ distributions

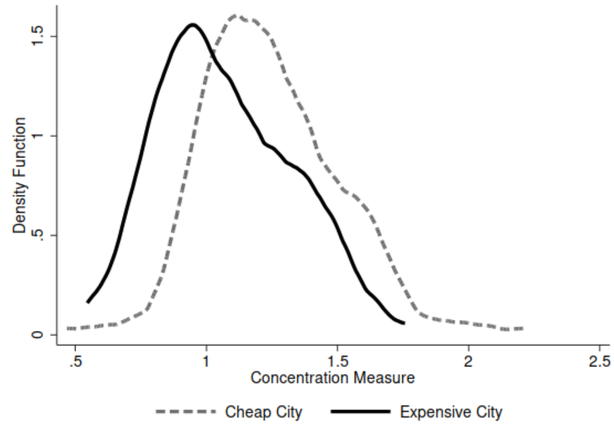
seen no clear change in concentration, and all other occupational groups have seen an increase in concentration. These results complement the findings regarding the location quotient, by indicating how the concentration of each occupation group has changed across cities. While these results are generally in line with what we should expect given our model's outcomes, we are not able to precisely link them to city characteristics. In order to do that, in the next section we follow Oyer and Schaefer (2016) and adapt the Ellison and Glaeser (1997) to create a city's skill concentration index.

B.3 Oyer-Schaefer (2016) Index

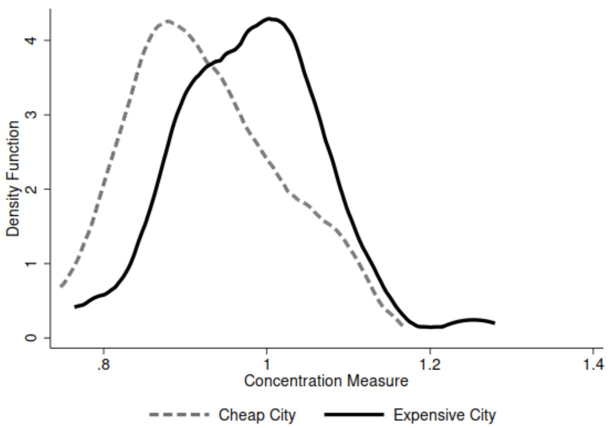
We now consider an adapted version of the EG concentration index based on Oyer and Schaefer (2016), which we call the Oyer-Schaefer index (henceforth OS index). Hence, denote ζ_j the OS concentration index for city j. To define this index, we first introduce some notation. Define $\tilde{x}_i$ as the overall share of workers of skill i in the economy, i.e., $\tilde{x}_i = \frac{M_i}{\sum_{l=1}^{N} M_l}$. Similarly, define $\tilde{s}_{ij}$ the



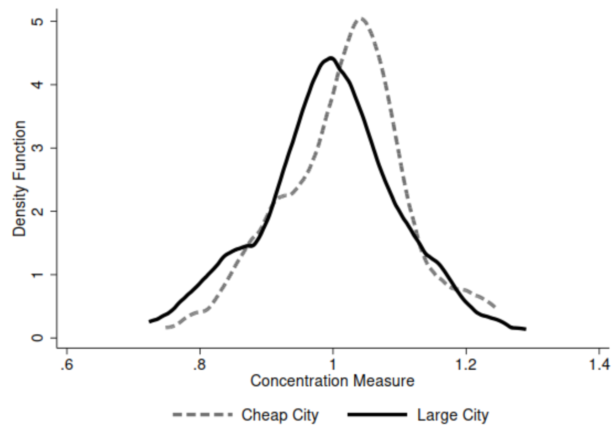
(a) Routine Manual: 1990



(b) Routine Manual: 2015



(c) Routine Cognitive: 1990



(d) Routine Cognitive: 2015

Figure OA-4: Routine occupations LQ distributions

share of workers of skill i in city j, i.e., $\tilde{s}_{ij} = \frac{m_{ij}}{S_j}$, where S_j is city j's labor force size. Then, the OS index is defined as:

$$\zeta_j = \frac{S_j}{S_j - 1} \frac{\sum_i (\tilde{s}_{ij} - \tilde{x}_i)^2}{1 - \sum_i \tilde{x}_i^2} - \frac{1}{S_j - 1} \qquad \text{(OA.3)}$$

Differently from the EG index, in the OS index we are able to compare the degree of concentration across cities with different housing costs. Unfortunately, we are unable to pin down the source of the increase/decrease in within-city concentration. In particular, we are unable to tie the changes in concentration to changes in the shares of each particular skill group. In this sense, although the EG and OS indexes complement each other, both have weaknesses and do not give a complete picture of the changes in concentration.

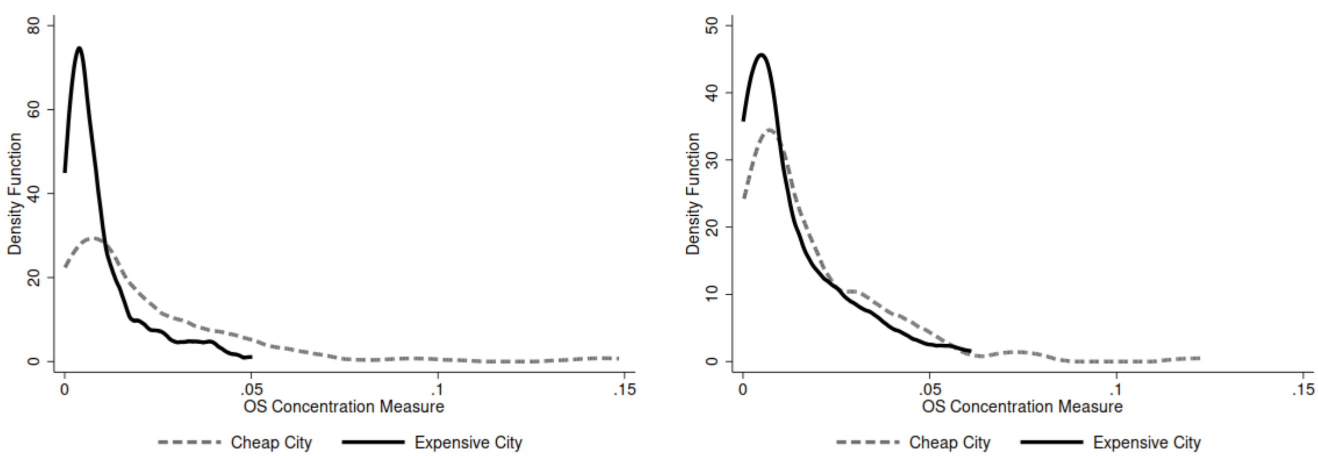
Table OA-7 presents the results for 1990 and 2015. As we can see, in both periods, cheap cities are consistently more concentrated than expensive cities, although the statistical significance of the difference has decreased over time. Furthermore, while cheap cities have seen a reduction in concentration, expensive cities have become more concentrated over time.

Table OA-7: OS index across city cost and time

Panel A: 1990					
	Mean	Median	St. Dev.	Min	Max
Expensive City	0.00955	0.00558	0.01041	0.00002	0.05026
Cheap City	0.02089***	0.01217†††	0.02476	0.00011	0.14851
Panel B: 2015					
	Mean	Median	St. Dev.	Min	Max
Expensive City	0.01293	0.00736	0.01395	0.00007	0.06114
Cheap City	0.017503**	0.01185††	0.01900	0.00029	0.12240

***,**,* represent significance at 1, 5, and 10% respectively in a two-tailed t-test of means. †††,††, † represent significant at 1, 5, and 10% respectively in a Wilcoxon rank-sum test of medians.

Finally, we present the changes in the density distribution of the OS index in Figure OA-5. Notice that Figures OA-5(a) and OA-5(b) corroborate the results from Table OA-7, showing an increase in concentration among expensive cities and a decrease in concentration among cheap cities.



(a) 1990

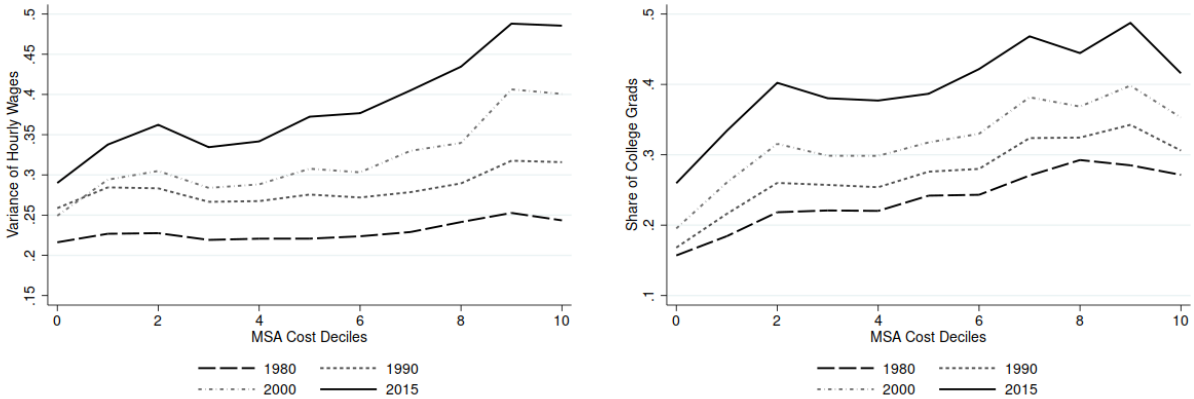
(b) 2015

Figure OA-5: Distribution of OS index across city sizes and time

C Wage Inequality Within and Between Cities

In this section we look at the patterns of wage inequality within and between cities and how these patterns changed over time and across occupational groups. As a result, we are able to infer the role of within-occupational-group worker heterogeneity in explaining the variations observed in the data.

First, as pointed out in the literature (see Baum-Snow and Pavan (2013), Eeckhout et al. (2014), and Santamarıa (2018), among others), large cities are more unequal and inequality has gone up over time. As we see in Figure OA-6a,[1] wage dispersion is larger in big cities.



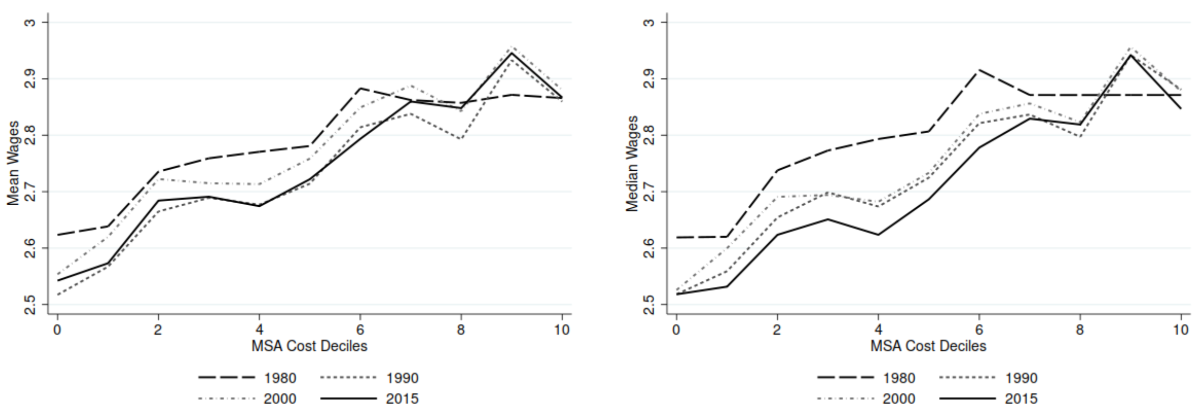
(a) Variance of Hourly Wages

(b) Share of College Graduates

Figure OA-6: Inequality within cities over time and by city's housing cost

Moreover, while we have seen that college attainment has been marginally higher in larger MSAs (Figure OA-6b), the results in Figure OA-6a still hold even after we control for several observable characteristics.

Instead, inequality *between* cities as measured by the city wage premium has not changed over time. Figure OA-7 shows that the increase in the mean and median wages with city housing cost has not changed significantly over time.[2]



(a) Mean Hourly Wages

(b) Median Hourly Wages

Figure OA-7: Inequality between cities: the Urban Wage Premium over time

Finally, we decompose the overall variance in wages in terms of a within- and between-city

[1]Observe that in Figures OA-6 and OA-7, as well as the figures in online appendix section C.1, we present deciles in terms of cities' cost of living, proxied by log(rent index) in 1980, and not in terms of the city size as in Baum-Snow and Pavan (2013) for example.

[2]In fact, once we control for observable characteristics, as presented in Appendix section C.1, differences over time in mean and median residual wages are even smaller.

contribution. Following the decomposition proposed by Lazear and Shaw (2009), the total variance in wages, σ^2, is given by

$$\sigma^2 = \sum_{j=1}^{J} s_j \sigma_j^2 + \sum_{j=1}^{J} s_j (\overline{w}_j - \overline{\overline{w}})^2. \tag{OA.4}$$

The first term on the RHS of equation (OA.4) is the within-city component of the variance. s_j is the share of workers in the economy employed in city j, while σ_j^2 is the variance of wages in city j. The second term on the RHS of equation (OA.4) represents the between-city component of the wage variance. In this expression, $\overline{w}_j$ is the mean wage in MSA j, and $\overline{\overline{w}}$ is the mean wage in the economy.

The results in Table OA-8 show that most of the wage dispersion is due to the within-city component (around 95 percent). Moreover, the decomposition in terms of within- and between-city components is persistent over time. Consequently, the contribution of each component to the overall increase in wage inequality has stayed proportional to each component's contribution to the overall dispersion. These results are preserved even when we focus on wage dispersion within occupational groups (See Table OA-9 in Appendix Section C.1) as well as when we control for observables (Tables OA-10 and OA-11 in Appendix Section C.1).

Table OA-8: Variance decomposition log hourly wages

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.237	0.226	0.011	95%	5%
1990	0.297	0.280	0.017	94%	6%
2000	0.336	0.320	0.017	95%	5%
2015	0.408	0.385	0.023	94%	6%

We need to keep in mind though that, while the bulk of wage dispersion is due to the within-MSA component, this does not mean that geographical components do not play a key role in explaining wage dispersion. As technology is adopted unevenly across space and workers and firms choose to search for workers and post jobs in different cities, these decisions affect both the within- and between-MSA components of wage inequality. Consequently, our decomposition exercise mostly says that, in terms of wage inequality, while cities vary in terms of wage inequality, the bulk of the wage inequality happens within the average city.

C.1 Residual Wage Distributions

We calculate residual wages as the residual of a Mincer regression. In particular, we estimate a separate Mincer regression for each year:

$$\log(w_{it}) = \alpha_t + \beta_t X_{i,t} + \varepsilon_{i,t} \tag{OA.5}$$

We include the typical controls in a Mincer regression (age, age squared, a gender dummy, and a full set of race fixed effects). We also control for educational groups (less than high school, high school graduate, some college, college and more), a dummy for foreign born, and industry groups. Results are qualitatively the same if we do not include industry or educational groups. Results are presented in Figure OA-8. As we can see, results are qualitatively the same as the ones presented in Figure OA-6a.[3] Similarly, we can calculate the mean and median residual wages, as well as the inter-quantiles residual wage differences.

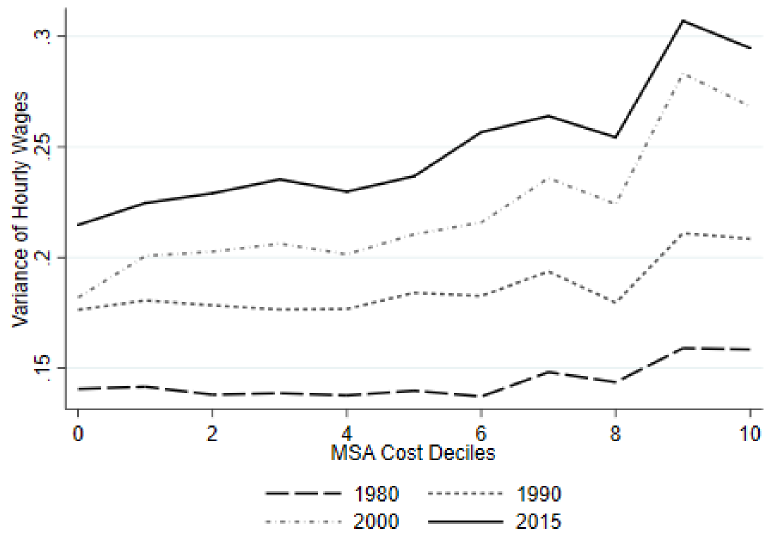


Figure OA-8: Variance Residual Wages

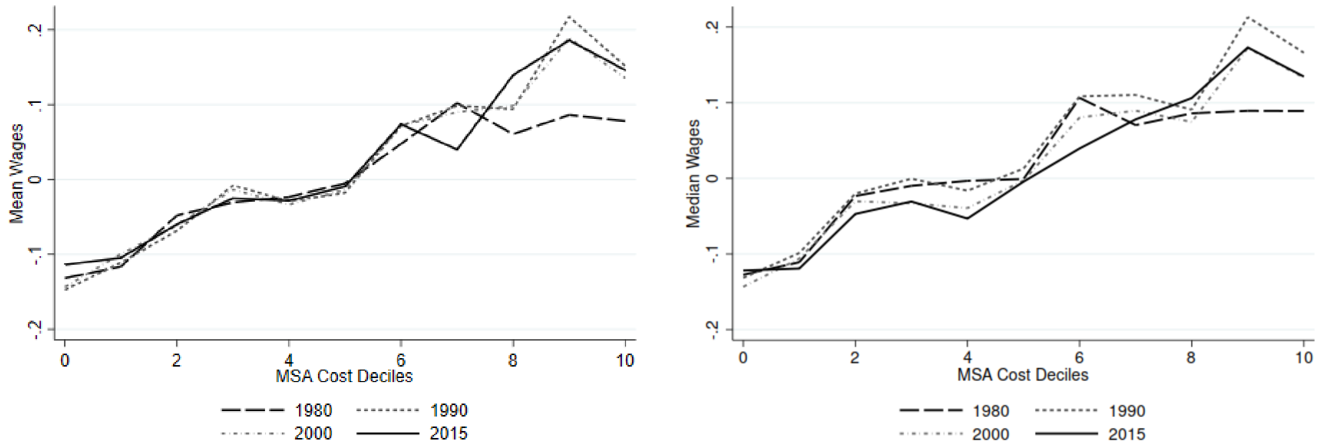
D Introducing Land and Firm Ownership

We have considered absentee land and firm owners up to now. In this section, we consider the case of land and firm ownership.[4] Following Fajgelbaum and Gaubert (2020), we consider that each type $\mathbf{s}$ worker in location j and occupation i earns a wage $w_{i,j}(\mathbf{s})$ and owns a fraction $b(\mathbf{s})$ of the national returns to fixed factors Π. Workers of different types may differ in their ownership of fixed factors, but they hold the same portfolio regardless of where they locate.[5] In this case, the income of an agent of type $\mathbf{s}$ in city j and occupation i, $I_{i,j}(\mathbf{s})$ (called expenditure in Fajgelbaum and Gaubert (2020)) is given by:

[3]Notice that, while our results are qualitatively the same, some of the controls absorb part of the contribution of city's cost of living to wage inequality. This result is similar to differences in the industrial composition of cities of different sizes explaining up to one-third of the city size effect, as pointed out by Baum-Snow and Pavan (2013).

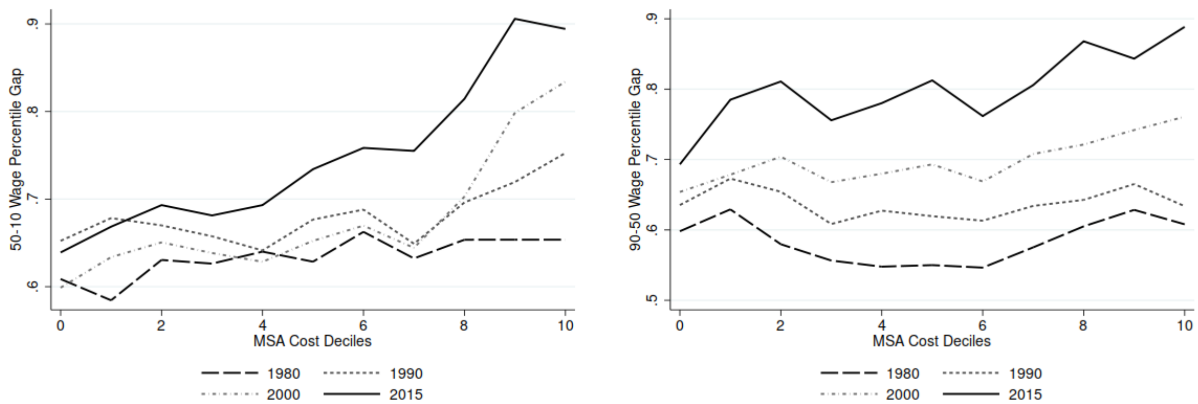
[4]Notice that because firms are immobile and there is no entry, firms have positive profits in equilibrium.

[5]According to Redding and Rossi-Hansberg (2017), distributing land rents locally to current residents – such as in Redding (2016) – generates inefficiencies because moving across locations imposes an externality on the rents received by other agents. To avoid this inneficiency and the interaction between location choice and rents, we follow Fajgelbaum and Gaubert (2020).



(a) Mean Residual Wages (b) Median Residual Wages

Figure OA-9: Mean and median residual wages across city costs and time



(a) 50-10 Percentile Gap (b) 90-50 Percentile Gap

Figure OA-10: Wage gaps across city costs and time

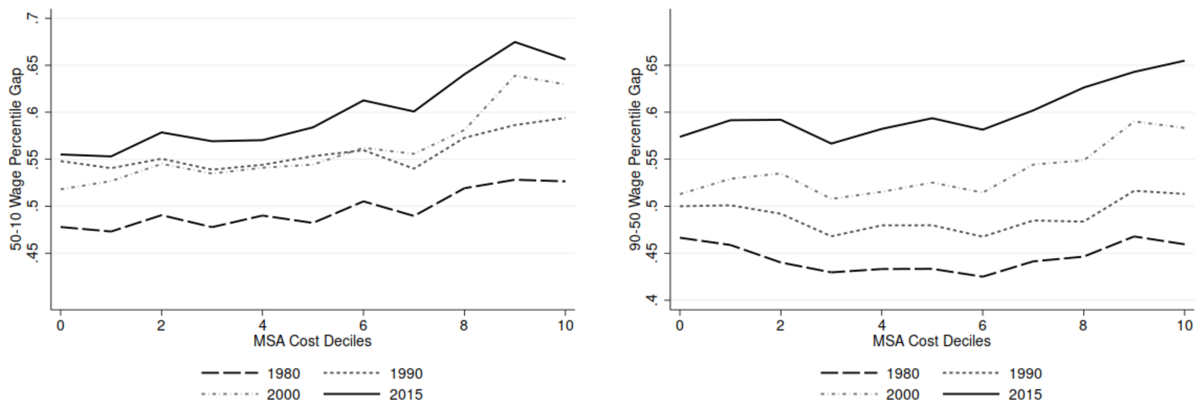
$$I_{i,j}(\mathbf{s}) = w_{i,j}(\mathbf{s}) + b(\mathbf{s})\Pi \tag{OA.6}$$

where:

$$\Pi = \sum_{j \in \mathcal{J}} \left\{ \pi_j + p_j H_j^S \right\} \tag{OA.7}$$

where π_j is the profit for representative firm in location j, p_j is the rent price in city j, and H_j^S the housing supply in city j.

Notice that this extension mostly changes the worker's problem. In particular, within a given city j and given a wage $w_{i,j} = \tilde{w}_{i,j} s_i$, a citizen chooses consumption bundles $\{c_{ij}, h_{ij}\}$ to maximize utility subject to the budget constraint:



(a) 50–10 Percentile Gap

(b) 90–50 Percentile Gap

Figure OA-11: Residual wage gaps across city costs and time

$$\begin{aligned} \max_{\{c_{ij},h_{ij}\}} u(c_{ij},h_{ij}) &= c_{ij}^{1-\alpha}h_{ij}^{\alpha} \\ \text{s.t. } c_{ij}+p_jh_{ij} &\leq I_{ij}(\mathbf{s}) \end{aligned} \tag{OA.8}$$

for all i, j. Solving for the competitive equilibrium allocation for this problem we obtain $c_{ij}^{\star} = (1-\alpha)I_{ij}(\mathbf{s})$ and $h_{ij}^{\star} = \alpha\frac{I_{ij}(\mathbf{s})}{p_j}$. Substituting the equilibrium values in the utility function, we can write $v(I_{ij}(\mathbf{s}), p_j) = (1-\alpha)^{(1-\alpha)}\alpha^{\alpha}\frac{I_{ij}(\mathbf{s})}{p_j^{\alpha}}$.

We consider the model with 4 skills and 3 cities. Moreover, we consider a production function such as:

$$A_jF(\mathbf{m}_j,\mathbf{k}_j,\mathbf{A}_j) = A_j\left\{ \sum_i A_{l,ij}^{\frac{\gamma_i}{\lambda}}\left[m_{ij}^{\gamma_i}+A_{k,i}k_{ij}^{\gamma_i}\right]^{\frac{\lambda}{\gamma_i}} \right\}^{\frac{1}{\lambda}}. \tag{OA.9}$$

and a competitive housing market. Housing supply follows the price-quantity schedule

$$p_j(H) = \phi_jH^{\epsilon_{p,j}}. \tag{OA.10}$$

In other words, we consider a simplified version of our general model, in which workers cannot choose their occupation and have no idiosyncratic preferences for location. To calibrate the parameters, we use the estimated parameters in our initial submission, i.e.:

Finally, we need to discuss how to properly pin down $b(\mathbf{s})$. In Fajgelbaum and Gaubert (2020), they identify worker types with observable skill groups. In particular, they divide workers in two skill groups: high-skill (college) and low-skill (non-college). They then combine data from ACS and BEA to construct $I_{i,j}$. Based on the average share of capital income in the MSA owned by high-skill workers being 0.52, they set $b(s)$. We follow a similar procedure for a larger group of worker types.[6] In particular, we assume that high-skill workers own 52% of the portfolio, mid-skill

[6] Another possibility would be to split according to the log-normal for non-routine cognitive skills. We could make the case that higher non-routine cognitive skills is related to parents' wealth, both due to education attainment of

Table OA-9: Variance Decomposition: Log hourly wages – Occupational groups

Routine Cognitive

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.209	0.202	0.008	96%	4%
1990	0.259	0.243	0.016	93%	6%
2000	0.281	0.265	0.015	95%	6%
2015	0.347	0.329	0.018	95%	5%

Non-Routine Cognitive

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.228	0.217	0.010	96%	5%
1990	0.275	0.259	0.016	94%	6%
2000	0.324	0.308	0.016	95%	5%
2015	0.373	0.348	0.024	94%	7%

Routine Manual

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.194	0.175	0.019	90%	10%
1990	0.236	0.221	0.015	94%	6%
2000	0.235	0.224	0.012	95%	5%
2015	0.261	0.251	0.011	96%	4%

Non-Routine Manual

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.211	0.197	0.015	93%	7%
1990	0.276	0.254	0.022	92%	8%
2000	0.277	0.263	0.015	95%	5%
2015	0.286	0.275	0.012	96%	4%

Table OA-10: Variance Decomposition: Log hourly residual wages

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.194	0.187	0.007	96%	4%
1990	0.228	0.216	0.012	95%	5%
2000	0.262	0.251	0.010	96%	4%
2015	0.286	0.276	0.010	96%	4%

offspring, as well as higher non-cognitive skills that boost offspring's likelihood of white collar jobs (Karagiannaki (2017) and Johnson (2020)).

Table OA-11: Variance Decomposition: Log residual wages – Occupational Groups

Routine Cognitive

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.178	0.172	0.006	97%	3%
1990	0.216	0.204	0.012	94%	6%
2000	0.243	0.233	0.010	96%	4%
2015	0.271	0.261	0.010	96%	4%

Non-Routine Cognitive

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.190	0.183	0.007	96%	4%
1990	0.228	0.216	0.012	95%	5%
2000	0.274	0.263	0.011	96%	4%
2015	0.294	0.282	0.013	96%	4%

Routine Manual

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.185	0.172	0.013	93%	7%
1990	0.203	0.191	0.012	94%	6%
2000	0.216	0.207	0.009	96%	4%
2015	0.236	0.229	0.007	97%	3%

Non-Routine Manual

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.184	0.176	0.008	96%	4%
1990	0.208	0.192	0.016	93%	7%
2000	0.220	0.209	0.011	95%	5%
2015	0.206	0.198	0.009	96%	4%

workers own 41%, and low-skill workers own 7%. Within occupation groups, the portfolio shares are evenly divided, regardless location.

Figure OA-12 shows the citywide occupation distribution by rent index for the cases of absentee owners (a) and profit portfolio (b). As we can see, the citywide occupation distributions are quite similar in both cases. In practice, since workers' income is not as dependent on location, low-rent cities become a bit larger. Similarly, in Table OA-13, we see how equilibrium rent indexes vary with local productivity in both cases. Again, the relationships are quite similar.

Table OA-12: Estimated Parameters 2015

Panel A: City level Parameters

Parameter	**low rent index**	**mid rent index**	**high rent index**
TFP A_j	59,000 (4200.0)	99,000 (12000.0)	120,000 (23000.0)
Measure of cities with A_j	154	75	24
Amenity a_j	1.0	1.2 (0.12)	1.6 (0.17)
House price shifter ϕ_j	0.059 (0.0079)	0.014 (0.0016)	0.0011 (0.00019)
Housing supply elasticity ϵ_j	0.48	0.69	1.1
Occupation Productivity $A_{l,ij}$			
non-routine manual	2.1 (0.2)	2.0 (0.21)	1.7 (0.2)
routine manual	3.0 (0.3)	2.9 (0.52)	3.9 (0.73)
routine cognitive	1.0	1.0	1.0
non-routine cognitive	1.0 (0.0088)	1.1 (0.017)	1.1 (0.025)

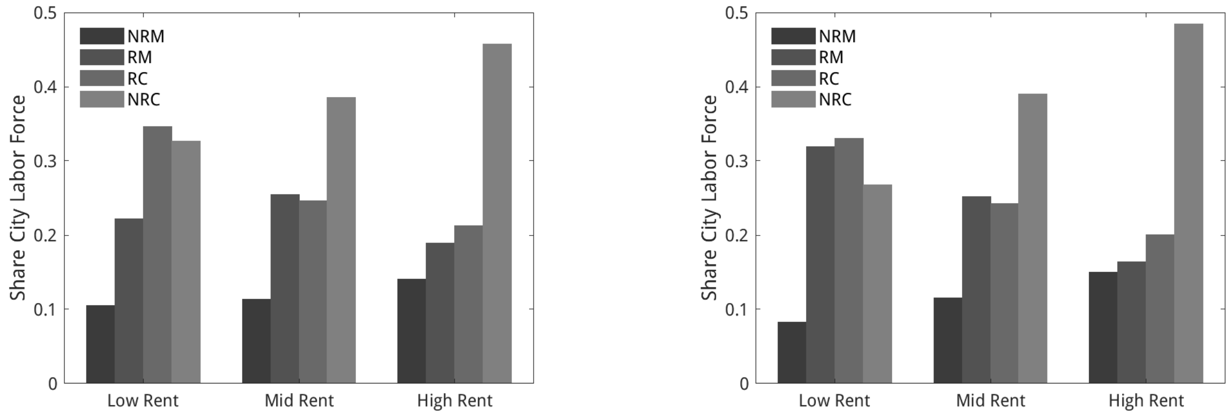
Panel B: Occupation level Parameters

	non-routine	routine	routine	non-routine
Parameter	**manual**	**manual**	**cognitive**	**cognitive**
Capital Productivity $\frac{A_{k,i}}{A_{l,i}}$	0.11	0.013	0.02	0.15
Capital-Labor substitution parameter γ_i	0 0.23	0.62	0.62	-0.079
Measure of Workers in Occupation M_i	8,283,695	14,018,560	14,655,767	27,399,913

Panel C: Additional Parameters

Parameter	**Value**	**Source/Explanation**
λ	-0.33	Occupation output elasticity $\frac{3}{4}$ (Goos et al., 2014; Lee and Shin, 2017)

Note: Standard errors in parentheses. Housing supply elasticity from Saiz (2010). See Appendix G for details.



(a) Absentee Landlords (b) Profit Portfolio

Figure OA-12: Skill distribution across cities: Absentee Landlords vs. Profit Portfolio

	Low TFP	**Mid TFP**	**High TFP**
Absentee Landlords	6.02	147.42	1,530.91
Household Portfolio	17.98	186.07	1,495.18

Table OA-13: Equilibrium Rent Index by Local TFP: Absentee Landlords vsl Profit Portfolio

E Additional Empirical Results: Weighted Regressions

Table OA-14: IT budget per worker – 2015

	(1)	(2)	(3)	(4)	(5)	(6)
	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)
MSA log rent index 1980	0.241***	0.140***			0.133**	0.139**
	(0.035)	(0.046)			(0.054)	(0.054)
MSA RC share 1980			0.189		0.045	0.148
			(0.376)		(0.385)	(0.378)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0580*	0.010	0.015
				(0.0312)	(0.038)	(0.038)
MSA Offshorability 1980						-0.124
						(0.112)
Housing supply elasticity		-0.001	-0.007	-0.0060	-0.001	-0.000
		(0.006)	(0.007)	(0.0067)	(0.006)	(0.006)
Amenities	No	Yes	Yes	Yes	Yes	Yes
MSA's Industry Mix Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	47.76	29.29	23.57	24.20	27.01	25.69
Adj. R^2	0.383	0.629	0.606	0.613	0.625	0.626
MSAs	217	217	217	217	217	217

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the metro area, adjusted for plant employment interacted with three-digit SIC industry. Each observation (an MSA) is weighted by its employment in 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table OA-15: Change in routine-cognitive share, 1990-2015

	Δrout-cog					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	-0.0329**	-0.0321***			-0.0201*	-0.0193*
	(0.0157)	(0.0095)			(0.0109)	(0.0111)
MSA RC share 1980			-0.3545***		-0.3097***	-0.2936***
			(0.0883)		(0.0919)	(0.1000)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				-0.0237***	-0.0110	-0.0103
				(0.0062)	(0.0078)	(0.0078)
MSA Offshorability 1980						-0.0181
						(0.0249)
Housing supply elasticity		-0.0032**	-0.0012	-0.0023*	-0.0024*	-0.0022
		(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
CMSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	4.40	28.56	32.18	27.68	32.34	33.09
Adj. R^2	0.105	0.684	0.700	0.684	0.713	0.712
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of routine cognitive occupations in the MSA's employed labor force between 1990 and 2015. Each observation (an MSA) is weighted by its employment in 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table OA-16: Wage ratios NRC-RC: 1990–2015

	$\Delta \ln\left(\frac{W_{NRC}}{W_{RC}}\right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.1248***	0.1533***			0.1383***	0.1283***
	(0.0293)	(0.0254)			(0.0304)	(0.0295)
MSA RC share 1980			0.7487***		0.6314***	0.4491*
			(0.2272)		(0.2255)	(0.2376)
MSA non-routine cognitive share 1980			0.3031**		0.1162	0.0105
			(0.1493)		(0.1883)	(0.1856)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0705***	-0.0029	0.0019
				(0.0228)	(0.0334)	(0.0331)
MSA Offshorability 1980						0.1893***
						(0.0678)
Housing supply elasticity		0.0003	-0.0061**	-0.0048	-0.0010	-0.0032
		(0.0031)	(0.0031)	(0.0030)	(0.0032)	(0.0032)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
CMSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	18.16	16.29	11.74	12.41	16.82	19.03
Adj. R^2	0.257	0.608	0.573	0.564	0.621	0.634
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the log ratio of nonroutine cognitive occupation and routine cognitive occupation real average wages between 1990 and 2015. Each observation (an MSA) is weighted by its employment in 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.