Skilled Scalable Services: The New Urban Bias in Economic Growth — Source link

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Published on: 29 Aug 2020 - Social Science Research Network (Munich: Center for Economic Studies and Ifo Institute (CESifo))

Topics: Urban bias

Opportunity & Inclusive Growth INSTITUTE

FEDERAL RESERVE BANK OF MINNEAPOLIS

INSTITUTE WORKING PAPER
No. 25

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Revised November 2020

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DOI: https://doi.org/10.21034/iwp.25
Keywords: Urban growth; High-skill services; Technological change
JEL classification: J31, O33, R11, R12

Skilled Scalable Services: The New Urban Bias in Economic Growth*

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First Version: March 2019
This Version: November 2020

Abstract

Since 1980, economic growth in the U.S. has been fastest in its largest cities. We show that a group of skill- and information-intensive service industries are responsible for all of this new urban bias in recent growth. We then propose a simple explanation centered around the interaction of three factors: the disproportionate reliance of these services on information and communication technology (ICT), the precipitous price decline for ICT capital since 1980, and the preexisting comparative advantage of cities in skilled services. Quantitatively, our mechanism accounts for most of the urban biased growth of the U.S. economy in recent decades.

Keywords: Urban Growth, High-skill Services, Technological Change
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*We thank Pol Antràs, David Autor, Costas Arkolakis, Gideon Bornstein, Laura Castillo-Martinez, Jonathan Dingel, Pierre-Olivier Gourinchas, Gordon Hanson, J. Bradford Jensen, Thomas Kemeny, Chris Moser, Michael Peters, Esteban Rossi-Hansberg, and Steve Redding for insightful comments and Serena Sampler for outstanding research assistance. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Eckert and Walsh thank the International Economics Section at Princeton University where some of this work was completed. The present version of this paper supersedes "Skilled Tradable Services: The Transformation of U.S. High-Skill Labor Markets."

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INTRODUCTION

For most of U.S. history, a central feature of economic growth was that it was faster in poorer regions (Barro and Sala-i Martin, 1992). Around 1980, something changed. Rich urban areas started seeing persistently faster income growth than the rest of the country. This new urban bias in growth is not well understood, but has had far-reaching economic and political consequences: house prices in urban areas have reached record highs, rural areas are struggling to attract high-skill workers, and the political rift between regions continues to deepen.

The urban bias has occurred alongside the more well-studied skill bias of recent growth, in which wages rose faster for more educated workers. The two biases are of comparable magnitude: between 1980 and 2015, the gap in the average wage between a worker with and without college degree grew by 44 percentage points, at the same time the average wage between a worker in the densest city (New York City, NY) relative to the median density city (Orlando, FL) grew by 32 percentage points.[1] The "skill biased technical change" literature argues that the faster wage growth of high-skill workers resulted in large part from their jobs being complemented by Information and Communication Technologies (ICT) in a time of rapid declines in the price of ICT capital (see Autor, Katz, and Krueger (1998), Krusell, Ohanian, Ríos-Rull, and Violante (2000), and Autor, Levy, and Murnane (2003)).[2]

This paper offers a unified perspective on the urban and skill biased growth of the U.S. economy in recent decades. We show that the urban bias resulted from the specialization of large cities in a group of service industries that rely disproportionately on high-skill labor and ICT capital. Statistically, the urban bias in the wage growth of these services accounts for *all* of the urban bias observed in the U.S. economy at large. We then use a quantitative spatial equilibrium framework to show that the aggregate decline in the price of ICT capital interacting with preexisting patterns of comparative advantage across cities explains the majority of the urban bias.

We infer which industries are particularly exposed to skill biased technological change by calculating measures of their reliance on high-skill labor and ICT capital in 1980. Four industries set themselves apart in the intensity of their use of both: Information (NAICS 51), Finance and Insurance (NAICS 52), Professional Services (NAICS 54), and Management of Companies (NAICS 55).[3] These service industries overwhelmingly concentrate in large cities, suggesting that cities offer them a distinct productive advantage. They also share a focus on creating and communicating information, a task which can be performed at larger scale using ICT capital. We call them Skilled Scalable Services.

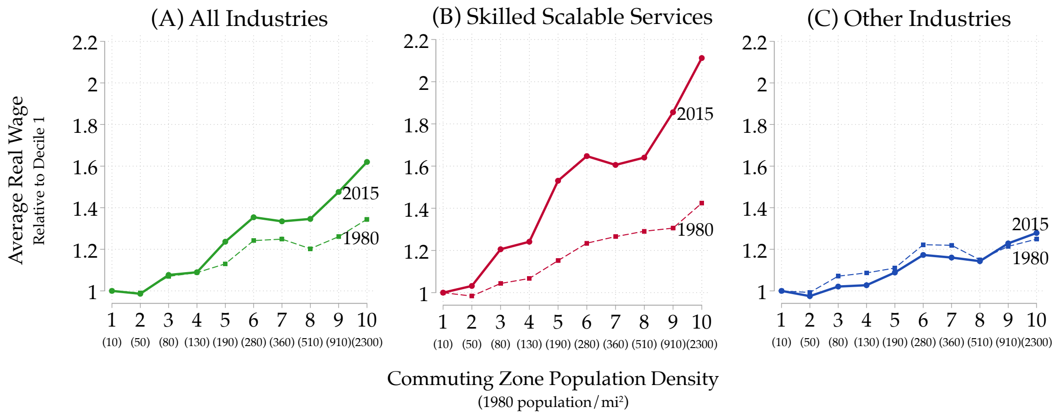
Statistically, Skilled Scalable Services account for all of the new urban bias observed in

[1] Approximately half of U.S. workers lived in cities less dense than Orlando, Florida, in 1980.

[2] Krusell et al. (2000) focus on equipment prices; the major driver of equipment capital price declines has been ICT (see Eden and Gaggl (2019)).

[3] These industries accounted for about 18% and 20% of aggregate U.S. employment in 1980 and 2015, respectively.

FIGURE 1: THE NEW URBAN BIAS



Notes: This figure shows average wages across commuting zone groups, in the aggregate and by industry group, plotted relative to their level in the first group. Data for average wages comes from the U.S. Census Bureau's Longitudinal Business Database (LBD) and is deflated using the Bureau of Labor Statistics' Consumer Price Index for Urban Consumers. We allocate each establishment in the LBD to a commuting zone (see Tolbert and Sizer (1996)) using its associated zip code identifier. To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density. Each group accounts for roughly one tenth of the U.S. population in 1980.

the U.S. economy since 1980. Figure 1 plots average wages across commuting zones ordered by population density in both 1980 and 2015. Comparing the wage-density gradient in 1980 and 2015 shows that average wages have risen faster in denser commuting zones. The other two panels reproduce the wage-density gradient for Skilled Scalable Services and for all other sectors separately; urban-biased wage growth appears only in the Skilled Scalable Services industries.[4]

We begin the paper by documenting that, between 1980 and 2015, Skilled Scalable Service industries showed patterns of growth previously associated with Skilled Biased Technical Change: fast *aggregate* wage growth, skill deepening of their workforce, and ICT technology adoption. Crucially, we show that all three of these trends displayed a striking urban bias, occurring fastest in the cities with the highest population density. These facts suggest that recent growth's urban bias is a feature of the same underlying shock as the skill bias: rapid improvements in ICT technology.

We then introduce a quantitative spatial equilibrium framework to measure the extent to which progress in ICT technology can account for the urban bias in recent growth. Our theory has three key components. First, firms in different sectors and locations can pay a fixed cost to adopt ICT technology in order to lower their marginal production cost. Second, the preexisting sectoral comparative advantage of a location influences a firm's technology adoption choice, with adoption more profitable in locations that offer productive advantages to a firm's sector. Third, as firms adopt ICT to increase their scale of production, the relative marginal products of high- and low-skill labor can change due

[4] We explore this in more disaggregated detail below. Figure A.1 in the Appendix replicates Figure 1 without binning commuting zones and with confidence intervals on the wage-density gradients.

to a non-homothetic production function. This captures the idea that at the firm level, investments in ICT technology may benefit high- and low-skill workers differently.

We model improvements in ICT technology as a decline in its price, following a long literature on investment-specific technical change (see Greenwood, Hercowitz, and Krusell (1997)). As the ICT price declines, more firms find it profitable to adopt the technologies. The returns to adoption are higher in locations with a comparative advantage in the firm's sector, causing both more firms in those locations to adopt the technology, and inframarginal firms to buy more capital conditional on adoption. Overall, sectoral labor productivity increases faster in locations with a more pronounced initial comparative advantage in that sector. The non-homotheticity in a firm's production function implies that as it adopts ICT, the optimal skill composition of its workforce changes. The result is that a decline in the ICT price gives rise to a labor demand shock that is both biased towards certain locations and skill groups. Upward sloping labor supply in each region, skill group, and sector translates the increase in labor demand into both skill and urban-biased wage growth, and compositional changes in the local workforce.

To estimate the model, we use U.S. data on output, establishments, wages, and employment at the commuting zone level. Changes in output and local skill intensity are used to calibrate the degree of non-homotheticity in production. Our estimates imply that the relative marginal product of high-skill labor rises with firm scale. We infer the sectoral comparative advantage of each commuting zone from the cross-section of sectoral employment shares and wages in 1980 (see Redding and Rossi-Hansberg (2017)).

We do not explicitly model the original sources of local comparative advantages, and the determinants of city industrial structure.[5] Instead, we focus on their interaction with the declines in the aggregate price of ICT capital in explaining the *dynamics* of wages, skill composition, and technology adoption across cities.

Our headline exercise consists of taking the model calibrated to the 1980 data, and then lowering the aggregate price of ICT capital (a single number) to trace out the path it takes in data from the Bureau of Economic Analysis (BEA). We study the resulting general equilibrium response of wages, workforce composition, and ICT adoption across regions. We find that the decline in the price of ICT capital alone can explain most of the new urban bias observed in the data by generating a strong urban and skill biased labor demand shock for Skilled Scalable Services industries.

Overall, our paper shows that growth in the service economy differs fundamentally from the broadly shared growth of the manufacturing era. Recent technical change has interacted with preexisting patterns of comparative advantage to produce growth that is strikingly biased towards both skilled workers and large cities. The unified perspec-

[5] The origins of cities' industrial structure are the subject of influential work in urban economics (see Duranton and Puga (2004) for a review). For example, Davis and Dingel (2019) construct a model with symmetric fundamentals that generates a spatial equilibrium in which larger cities exhibit better opportunities for idea exchange. As a result, cities have disproportionate employment in tradable industries, and its workforce is more skilled and devotes more time to ideas exchange than workers elsewhere. Ahlfeldt, Albers, and Behrens (2020) provide another recent study about the determinants of Skilled Scalable Service specialization.

tive Skilled Scalable Services offer on two of the most salient dimensions of inequality is likely to be an important avenue for future research.

Related Literature. A large literature has documented changes in the U.S. wage structure since 1980 that have favored skilled workers and increased income inequality.[6] The literature has identified skill biased technical change as the leading explanation for these changes (e.g., Autor et al. (1998) and Krusell et al. (2000)) with globalization also playing a role (e.g, Autor, Dorn, and Hanson (2015) and Burstein and Vogel (2017)). We contribute to this literature by showing that the same forces that explain recent growth's skill bias can also explain its urban bias. Our unified perspective on the skill- and urban-biased impact of recent technological change implies that regional inequalities, like inequalities between skill groups, are an integral part of ICT-driven economic growth.[7] Furthermore, our paper is the first to highlight the role of a small group of skill-intensive service industries as drivers behind the skill- and urban-biased shifts in the U.S. economy.[8]

Barro and Sala-i Martin (1992) is the seminal paper documenting convergence of average wages across U.S. states since 1840. The end of wage convergence around the 1980s, has first been documented by Berry and Glaeser (2005) and Moretti (2012). Follow-up work links the end of wage convergence to housing supply constraints (Ganong and Shoag (2017)), local agglomeration economies becoming more skill biased (Giannone (2017)), and changes in firm dynamism (Rubinton (2019)).[9] Our paper is the first to show that a small group of service industries is driving the end of wage convergence. We also provide a theory specific to these services that explains the end of wage convergence as a function of observable quantities and prices interacting with the existing industrial structure of regions.

Beaudry, Doms, and Lewis (2010) study ICT technology adoption across metropolitan areas. In their stylized model firms adopt faster where the relative price of skill is low. As a result, once relative skill prices are equalized across regions, there is no more biased adoption of ICT technology. Raw correlations between city size and the skill premium are positive in every decade since 1980 (see Baum-Snow and Pavan (2013)); and skill premia appear to have diverged across regions in the last decades, not converged (see

[6]See Katz and Murphy (1992), Bound and Johnson (1992), Juhn, Murphy, and Pierce (1993), Card and DiNardo (2002), Autor et al. (2003), Lemieux (2006), and Autor, Katz, and Kearney (2008) for seminal contributions. Acemoglu and Autor (2011) provides a synthesis of this literature.

[7]Baum-Snow and Pavan (2013) are among the first to argue for a distinct role of cities in generating the increase in inequality.

[8]Our paper also contributes to a recent literature on ICT technologies and scale. Lashkari, Bauer, and Boussard (2018) show directly, using French micro data, how ICT helps firms increase their scale. Autor, Dorn, Katz, Patterson, and Van Reenen (2020) and Aghion, Bergeaud, Boppart, Klenow, and Li (2019) argue that the falling ICT price has led to "superstar firms" that scale up to dominate markets. We show that a small group of spatially-concentrated service industries displays disproportionately strong ICT adoption and that the "superstar locations" in which they locate are pulling away from the rest of the country.

[9]There is also a large literature documenting the *implications* of the urban and skill biased labor demand growth of recent decades for changes in amenities, house prices, misallocation, the organization of production, polarization, and the retail environment (see Diamond (2016), Couture, Gaubert, Handbury, and Hurst (2019), Hsieh and Moretti (2019), Santamarıa (2018), Davis, Mengus, and Michalski (2020), and Almagro and Domınguez-Iino (2019)).

Baum-Snow and Pavan (2013), Giannone (2017), Eckert (2019)). To explain these facts, our model and empirical work suggests instead that a broader notion of the comparative advantage of dense locations in Skilled Scalable Services activities is needed. In contrast to their paper, we also take our model to the data to quantify the strength of its central mechanism.

Eckert (2019) identifies high-skill tradable services as driving the uneven growth of the skilled wages premium across U.S. cities since 1980.[10] He uses a quantitative trade model to argue that declining trade costs for such services amplified existing patterns of comparative advantage across regions. Relative to his paper, we document the urban-biased growth patterns of these services more broadly and provide a more general theory of how ICT adoption allowed these services firms to scale up their operations drawing on their comparative advantage in cities.

1. Defining Skilled Scalable Services

Data Overview. In our analysis, we draw on the largest and most widely-used sources of U.S. employment data: the Longitudinal Business Database (LBD), the U.S. Decennial Census and American Community Survey data (Census), and the Quarterly Census of Employment and Wages (QCEW). We map all data to consistent 2012 NAICS industry classifications (Fort and Klimek, 2016) and stable commuting zone delineations (Tolbert and Sizer, 1996).

We use two sources of data on ICT capital stocks by industry. The BEA's Fixed Asset tables report capital stocks by industry. We supplement this data with two restricted-use surveys conducted by the U.S. Census Bureau: the Annual Capital Expenditures Survey (ACES) and Information & Communication Technology Survey (ICTS). Aggregate industry value added data comes from the BEA National Industry tables. Appendix D contains more detail on sample selection, data sources, and data processing.[11]

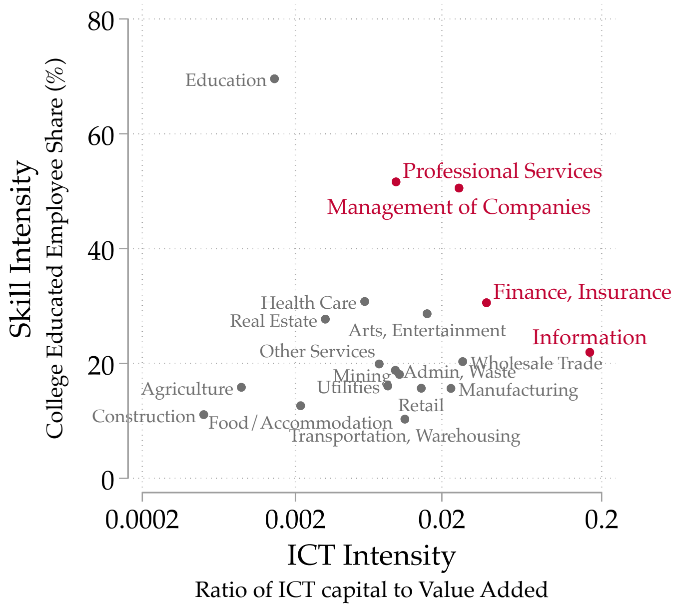
Defining Skilled Scalable Services. To identify which industries are particularly exposed to skill biased technical change, we compute measures of their reliance on high-skill workers and the ICT capital, respectively. In particular, for all 2-digit NAICS industries we calculate the college share among its employees ("skill-intensity"), and the value of an industry's overall ICT capital normalized by its value added ("ICT intensity") in 1980.[12] Figure 2 plots skill intensity against ICT intensity for all 2-digit NAICS indus-

[10] There is a nascent literature on the role of services in explaining the recent changes in spatial organization of economic activity. Hsieh and Rossi-Hansberg (2019) document that recently "chain" service firms such as hospitals or supermarkets, aided by ICT technology, have expanded their stores into small and mid-sized cities. Headquarters of such firms are Skilled Scalable Services establishments and so their paper complements ours showing concrete instances of how Skilled Scalable Services establishments in big cities use ICT to scale up their operations.

[11] In the Online Appendix D.4, we also compare our three main data sources to one another. While there are some level differences, the spatial and time-series trends are nearly identical.

[12] It is important to emphasize that the NAICS classification system applies to establishment, not firms: different establishments of the same firm can have different industry classification. For example, the headquarters of Walmart belongs to the "Management of Companies" NAICS code, while their stores belong to

FIGURE 2: DEFINING SKILLED SCALABLE SERVICES USING 1980 DATA



Notes: This figure shows the ICT intensity of all 2-digit NAICS industries graphed against their skill intensity. We compute ICT intensity as the value of a sector's ICT capital stock relative to its value added using the BEA Fixed Asset and Value Added Tables, and skill intensity as the share of employees in the sector with a college degree or higher using the Population Census/ACS. We replace BEA value added data with QCEW payroll for the education sector, as the total value added is less than the reported QCEW payroll figure. This will overestimate the ICT intensity of that sector, as we assume that the only value added in education comes from labor payments. We report data for 1980.

tries. Four service industries set themselves apart from all others by being at the same time very skill- and ICT-intensive. These are "Professional, Scientific, and Technical Services", "Management of Companies", "Information", and "Finance and insurance." We refer to this group as Skilled Scalable Services – or SSS for short – throughout the paper.

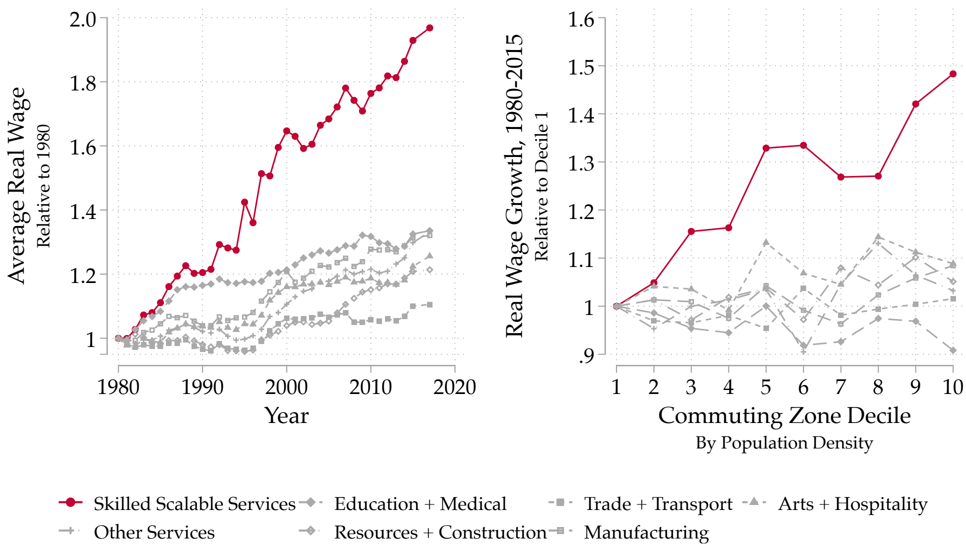
Skilled Scalable Services accounted for about 17% of aggregate employment in the U.S. economy in 1980, a number that has little in subsequent decades. . Employment shares in Skilled Scalable Services increased rapidly in local population density – more than any other 2-digit industry – both in 1980 and in 2015.[13] This suggests that cities with higher population density have long offered distinct productive advantages to Skilled Scalable Services industries.[14]

"Retail." In the Online Appendix, we show that this convention leads to differences between self-reported industries in the Census, and administrative industry classification from the LBD. Headquarters workers tend to state "Retail" even if they work at a retailer's headquarter establishment.

[13] See Figures A.3 and A.4 in the Appendix.

[14] In Figure A.3 in the Appendix, we show the local employment shares of Skilled Scalable Services industries and all other 2-digit NAICS industries for all commuting zone deciles in both 1980 and 2015. Table A.1 in the Appendix also lists the Skilled Scalable Services employment shares for each density decile directly.

FIGURE 3: SKILLED SCALABLE SERVICES WAGE GROWTH



Notes: The left panel shows average real wages by sector relative to 1980. The right panel shows wage growth by sector across commuting zone groups of increasing density. The data come from the QCEW (left) and the LBD (right). We allocate each establishment in the LBD to a commuting zone (see Tolbert and Sizer (1996)) using its associated zip code identifier. To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density each accounting for about one tenth of the U.S. population in 1980. The wage data is put in real terms by deflating nominal figures with the BLS CPI-U.

2. THE URBAN BIASED GROWTH OF SKILLED SCALABLE SERVICES

We now show that in the aggregate SSS industries exhibit growth patterns generally associated with skill biased technical change: rapid wage growth, skill deepening, and ICT adoption. However, we also document that all three of these patterns occur disproportionately in cities with high population density. Overall, these facts suggest that the urban and skill bias in the recent growth have a common cause.

Fact 1. *Skilled Scalable Services have seen rapid and urban-biased wage growth since 1980.*

The left panel of Figure 3 shows the growth in average real wages in different sectors of the U.S. economy between 1980 and 2015.[15] Average wages in SSS industries grew three times faster than those in other sectors of the economy. While all other sectors exhibit very similar wage growth paths, the SSS industries appear to be on a different trajectory altogether.

The right panel shows the urban bias of SSS wage growth in this period. To construct the graph, we form ten groups of commuting zones, ordered by population density in 1980 so that each group accounts for one tenth of the U.S. population in 1980.[16] We

[15] Figure A.5 replicates the left panel for all 2-digit NAICS industries individually. Each industry that is part of the SSS sector individually grows faster than all non-SSS industries, too.

[16] Table A.2 in the Appendix shows the corresponding deciles of the 25 largest commuting zones in the

compute average wage growth across establishments in each industry and commuting zone group between 1980 and 2015. Finally, we divide wage growth in each commuting zone group by the wage growth in the least dense group of commuting zones for each industry.

SSS wage growth is sharply increasing across density groups, with growth being 50% faster in the densest commuting zones compared to the least dense. No other sectors' wage growth exhibits such an urban bias.

The urban biased growth of SSS industries has changed the overall wage-density gradient of the U.S. economy (see Figure A.1 in the Appendix). In 1980, both SSS and the rest of the economy displayed a moderate urban wage gradient, where a doubling of density implied a 5% and 7% increase in wages, respectively. In 2015, the urban wage gradient for most of the economy was barely changed from 1980, while for SSS, it had risen to 15%.

Naturally, *average* wage growth in a sector and location can reflect either wage growth within education groups or changes in the education composition of the work force. Our second fact documents these compositional changes.

Fact 2. *Skilled Scalable Services have seen rapid and urban-biased skill deepening since 1980.*

The left panel of Figure 4 shows the evolution of the ratio of college workers to non-college workers by industry. Since 1980, this ratio has increased by a factor of more than three in SSS, and by one half in most other sectors.[17] So while the economy overall became more skill-intensive, SSS did so much faster than other sectors, which all showed similar trends.

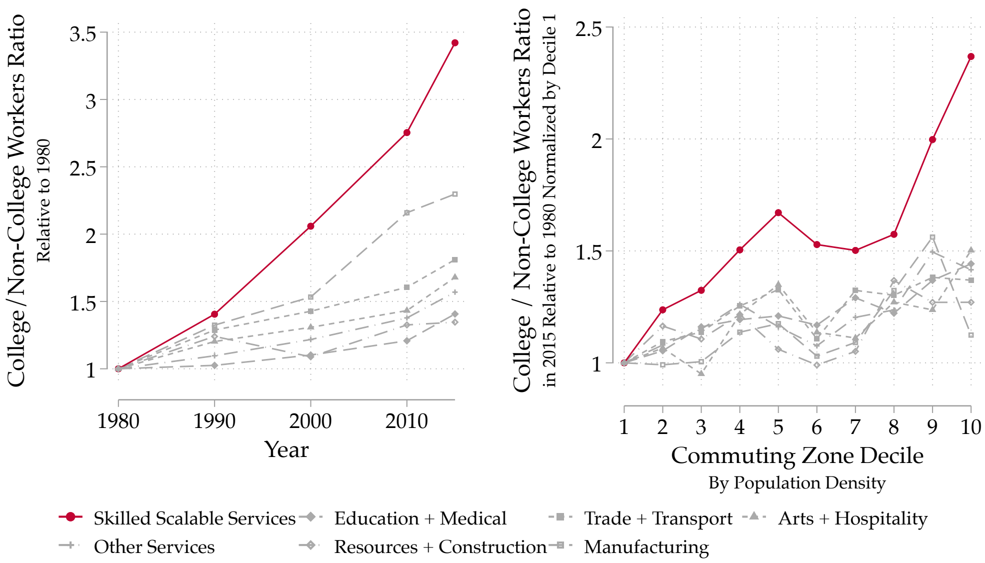
The right panel of Figure 4 shows the urban bias in the skill deepening. Skill deepening was somewhat faster in denser commuting zones for all industries. However, SSS industries set themselves apart, exhibiting a much stronger urban bias in their skill deepening than the rest of the economy.

The strong skill deepening in SSS suggests that part of the wage growth in Fact 1 is *compositional*. In Appendix B, we decompose changes in average wages into changes *within* and *across* four education groups: high school or less, some college, college, and more than college. Wage growth within each education group accounts for more than half of SSS wage growth between 1980 and 2015, both in the aggregate and within each commuting zone group. The compositional changes of the SSS workforce explain about

United States. In supplementary material we provide the complete mapping of all commuting zones to density deciles. An alternative way to construct this graph is to order commuting zones by increasing population *size*. Figures using population size instead of population density appear very similar to those shown throughout the paper.

[17] Skill deepening in manufacturing differs from the other non-SSS industries for two reasons. First, manufacturing employment for high- and low-skill workers is declining in absolute terms in this period. However, low-skill employment is declining faster, causing the ratio of college to non-college workers to increase. Second, Figure 4 is constructed from Decennial Census data. Comparisons between the administrative data from the LBD and the survey data from the Decennial Census suggest that many workers in manufacturing headquarters are falsely assigned to a manufacturing industry code instead of the headquarter code which is part of SSS. The Online Appendix contains detailed comparisons of these data sets.

FIGURE 4: SKILLED SCALABLE SERVICES SKILL DEEPENING



Notes: The left panel of this figure shows the ratio of the number of workers with at least a college degree to the number of workers without a college degree in each decade and sector, relative to 1980. The right panel shows the same ratio calculated instead for each commuting zone group and sector, relative to 1980 within each group and relative to the group with the least dense commuting zones. We allocate each worker in the Census to a commuting zone (see Tolbert and Sizer (1996)) via their PUMA code using the crosswalk provided by Autor et al. (2003). To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density each accounting for roughly one tenth of the U.S. population in 1980.

quarter of the wage growth, with a correlation component accounting for the remainder. Furthermore, the within education group component of wage growth exhibits a much stronger urban bias than its other components.

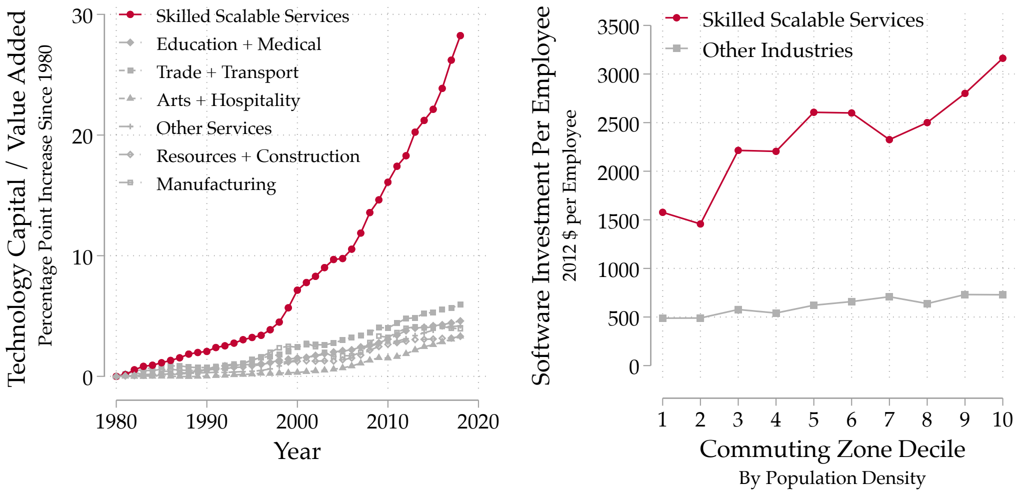
Figure A.2 displays the wage growth by education group and industry across commuting zones between 1980 and 2015. Both high- and low-skill workers experienced urban biased wage growth in SSS, but this bias was more pronounced for skilled workers. Neither high- nor low-skill workers saw a bias in other industries. In all industries, wage growth was faster for skilled workers. Notably, low skill workers in SSS experienced approximately the same average wage growth as high skill workers in other industries.

Fact 3. *Skilled Scalable Services have seen rapid and urban-biased ICT adoption since 1980.*

In defining SSS, we focused on skill-intensive industries that already had a relatively high amount of ICT capital in 1980. Since then, SSS industries have adopted ICT technology capital more than all other industries. For each 2-digit NAICS industry, we compute the value of its ICT capital stock (software and hardware) normalized by its value added. The left panel of Figure 5 shows the percentage point change in this measure between 1980 and 2015.[18] For SSS the normalized capital stock rose from 0.05 in 1980 to around

[18]Figure A.6 in the Appendix reports the same statistic for each individual 2-digit NAICS industry. It shows that the disproportionate adoption of ICT capital occurs in each of the four SSS industries individually. Each one of them adds significant more percentage points than any other sector in the U.S. economy.

FIGURE 5: SKILLED SCALABLE SERVICES ICT CAPITAL ADOPTION



Notes: Data for the left panel comes from the BEA Underlying Asset Tables ("Fixed-Cost Net Capital Stock of Private Nonresidential Fixed Assets"), and the right panel uses the Census Bureau ACES Survey and the LBD. We obtain industry-level value added data from the QCEW. The left panel of the figure shows the value of a sector's ICT capital stock that belongs to either Computerized Hardware Equipment or Software Intellectual Property relative to its value added. The right panel shows average software investment allocated to the establishment level, calculated by apportioning a firm's software investment to establishment in proportion to employment. We then aggregate all establishments in a commuting-zone-industry using firm sampling weights for 2007-2012. We allocate each establishment in the LBD to a commuting zone (see Tolbert and Sizer (1996)) using its associated zip code identifier. To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density each accounting for roughly one tenth of the U.S. population in 1980.

.30 in 2015.

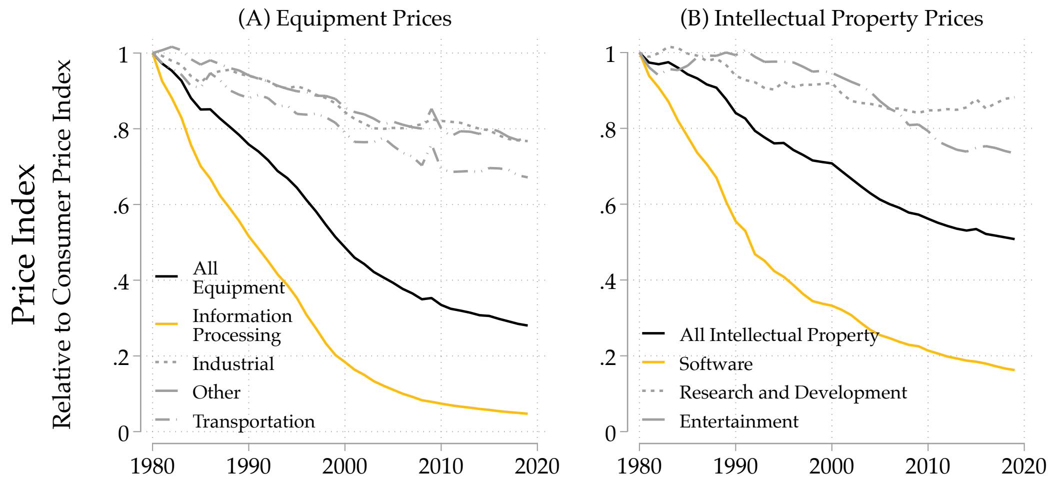
In the right panel of Figure 5, we plot software investment per employee across commuting zones of increasing density. SSS establishments in denser locations invested more than twice as much in software per employee than SSS establishments in the least dense commuting zones. Furthermore, non-SSS industries do not exhibit a significant urban bias in their investments. Lastly, SSS establishments in all locations have invested more than three times as much per employee than other industries.[19]

Discussion. Together, these three facts paint a picture of an important change in the nature of U.S. economic growth. They show that the SSS industries have seen explosive wage growth, become much more skill-intensive, and adopted ICT capital much faster than the rest of the U.S. economy. Crucially, all three of these developments show a distinct urban bias.

These trends are not driven only by education or certain occupations within SSS. We show in the Appendix that workers generally experienced urban-biased growth if they worked in SSS and mostly did not if they worked in other industries, regardless of edu-

[19]To construct this graph we rely on a survey conducted by U.S. Census on firms between 2007 and 2012. To construct the figure we average ICT investments over multiple waves of the survey, and allocate software to a firm's establishments in proportion to employment.

FIGURE 6: THE DECLINE OF THE PRICE OF ICT CAPITAL



Notes: The left panel of this figure plots the price of equipment investment from 1980-2018 relative to the consumer price index. The right panel replicates that plot for intellectual property investment. The data used are the BEA Asset Price Data and BLS Consumer Price Index for all Urban Consumers (CPI-U).

cation and occupation.[20] In the Online Appendix, we provide a more detailed analysis of SSS wage premia across occupational and educational groups.

Our facts point towards a common explanation for the urban and skill bias in recent economic growth: widespread ICT adoption in the U.S. economy, and in SSS in particular. Over the last few decades, these technologies have experienced dramatic price declines, unmatched by any other investment or consumption good. The left and right panel of Figure 6 show the major components of the BEA's equipment price index and intellectual property price index, respectively. Since 1980 equipment prices for information processing equipment have dropped by a factor of 20, while software prices have declined almost as fast. The other components of the indices show only modest declines.

A wide literature has pointed out that ICT is complimentary to high-skill labor (see, e.g., Autor et al. (2003)). As a result, adoption of ICT in SSS can rationalize both its fast wage growth and the disproportionate skill deepening in the *aggregate*. However, classical treatments of skill biased technical change (e.g., Krusell et al. (2000)) do not speak to the strong urban bias in wage growth, skill deepening, and ICT adoption. We now propose a theory that argues that the urban bias is the result of an interaction of the aggregate ICT price decline with the persistent comparative advantage of certain regions in SSS, which made ICT investment more profitable in those regions.

[20]Giannone (2017) shows that more educated worker have seen faster wage growth in larger cities since 1980. Rossi-Hansberg, Sarte, and Schwartzman (2019) show that workers in cognitive non-routine CNR) occupations have also seen faster wage growth in bigger cities. Figure A.7 replicates the right panel of Figure 3 for college-educated workers within SSS and outside SSS, we find that for non-SSS college-educated workers there is almost no urban bias in recent wage growth. Likewise, when we recompute the figure for CNR occupation workers within and outside SSS, we find that CNR workers outside SSS have not experienced an urban bias in their wage growth. Table A.3 presents regression estimates of the density bias for different education and occupation groups within and outside of SSS supporting these findings.

3. A MODEL OF SKILLED SCALABLE SERVICES

Our theory combines a firm model with a fixed cost technology (see Bustos (2011) and Yeaple (2005)) and a non-homothetic CES production function which causes firms to change the relative intensity with which they use different types of labor as the expand their scale (see Trottner (2019) and Lashkari et al. (2018)).[21] We embed these firms into a quantitative spatial equilibrium model in the spirit of Allen and Arkolakis (2014) and Redding (2016) with workers of different skill types that choose their location and sector of work.[22]

3.1 Description of the Mechanism

We model ICT as a fixed cost technology whose adoption decreases the marginal cost of production . The fixed cost of installing ICT and the per unit price of ICT capital are the same across locations. However, locations differ in their comparative advantage in SSS, and these comparative advantage differences translate into differences in the return to ICT adoption across locations. At the same time, ICT adoption can change the optimal skill composition of a firm's workforce. When we take the model to the data we find that ICT adoption increases a firm's reliance on high-skill relative to low-skill workers, and that denser cities have a comparative advantage in SSS production.[23]

In this setting, changes in the price of ICT capital leads to its disproportionate adoption in the cities with the highest population density. More SSS firms adopt ICT in these locations, and adopting firms also purchase more ICT capital conditional on adopting. The adoption of ICT capital changes firm scale and leads the firms to demand more high-skill workers relative to low-skill workers. Together these two effects translate a uniform decline in the aggregate ICT price into a urban and skill biased labor demand shock.

Workers choose their location and sector of employment. Their idiosyncratic preferences for where to work generate an upward sloping labor supply curve within each location-sector pair within each skill group. In equilibrium, the labor demand shock draws high-skill workers into cities and SSS industries, and raises their wages.

3.2 The Model

The economy consists of a set of discrete locations $r = 1, ..., R$. Workers have one of two levels of skill e; we refer to these workers types as high- and low-skill. There is a measure $\bar{H}$ and $\bar{L}$ of workers of high ($e = H$) and low ($e = L$) skill type, respectively. Workers

[21] Comin, Lashkari, and Mestieri (2020) use the non-homothetic CES aggregator as a utility function to model the effects of rising incomes on shifting sectoral demand.

[22] See Redding and Rossi-Hansberg (2017) for an overview of the class of quantitative spatial models.

[23] In Section 1 above we showed that SSS industries have always been heavily concentrated in dense cities. In a world of competitive labour markets, these specialization differences reveal that denser cities offer distinct productive advantages to SSS industries. From the point of view of an individual firm, location-specific productive advantages in a location increase the net return to ICT investments in that location, regardless of their precise origin.

choose a location r and a sector $s = 1, ..., S$ to work in. Output within each location and industry is produced by a set of heterogeneous firms, indexed by f and owned by a mass of location-less capitalists. The environment is static and all markets are perfectly competitive.

Firms. Firm f uses high- and low-skill labor, h_f and l_f, to produce a homogeneous, freely traded sectoral good. The quantity of output produced by firm f, y_f, is implicitly defined by a non-homothetic CES production function,

$$y_f = \tilde{z}_f^{1-\gamma} \left(\alpha_{r,s}^H y_f^{\frac{\epsilon^H}{\sigma\gamma}} h_f^{\frac{\sigma-1}{\sigma}} + \alpha_{r,s}^L y_f^{\frac{\epsilon^L}{\sigma\gamma}} l_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma\gamma}{\sigma-1}}, \tag{1}$$

where $\tilde{z}_f$ denotes *firm productivity* and the $\alpha_{r,s}^H$ and $\alpha_{r,s}^L$ terms indicate sector-specific *location productivties*.[24] The parameter $\sigma > 0$ denotes the elasticity of substitution between labor inputs, while $\gamma \in (0, 1)$ indexes the strength of diminishing returns to labor inputs. Importantly, the symbols ϵ^H and ϵ^L denote scale parameters which govern the marginal productivity of each type of labor at different levels of output y_f.[25] These parameters regulate how the optimal skill composition of production *changes* as the scale of production increases.

Firm f's productivity, $\tilde{z}_f$, consists of two components. The first is a fixed component denoted by z_f, which we refer to as *firm efficiency*. The second component is determined by a firm's decision to invest in ICT technology. Firms that pay a fixed cost C can purchase an amount of ICT capital k_f at unit cost p^K. After investing, their productivity increases by a factor of $(1 + \mu_s k_f^\beta)$ where the terms $\beta < 1$ and μ_s both control how useful ICT is in increasing firm productivity in sector s.[26] Overall, firm f's productivity is given by:

$$\tilde{z}_f = \begin{cases} z_f & \text{if do nothing} \\ z_f(1 + \mu_s k_f^\beta) & \text{if pay } C\text{, purchase } k_f. \end{cases} \tag{2}$$

In order to produce in location r, firms must buy a local building. All buildings are identical, and supplied by a local construction sector described below. After a firm has purchased a building, it draws its efficiency z_f from a distribution $G(z)$.

A national, representative firm aggregates sectoral outputs into a homogeneous final

[24] We take the location productivity as external to the firm. The location productivity terms flexibly parameterize the sectoral comparative advantage of a location, allowing it to differ across education groups as well. There is a large urban literature exploring the micro-origins of productivity differences across cities, such as Davis and Dingel (2019), Davis and Dingel (2020), and Duranton and Puga (2004).

[25] The non-homothetic CES production function is strictly more general than the standard CES production function. For $\epsilon_H = \epsilon_L = 0$ we recover a constant returns to scale CES production function. We chose this more flexible specification since the CES function of Krusell et al. (2000) generates too much growth in labor demand in the SSS industries as the price of ICT capital falls. We provide more details and a discussion in the Online Appendix. A parameter restriction on γ and $\{\epsilon_H, \epsilon_L\}$ is required to ensure that the cost function of the firm is convex. We assume this restriction holds throughout the analysis below.

[26] There is ample evidence that ICT capital is not complimentary to all types of work and enhances the productivity types of work to different degrees (see Autor et al. (2003)). Bessen (2017) provides context for the fixed cost modelling choice: ICT adoption is often associated with proprietary software investments that cost millions of dollars.

good, according to the production function:

$$Q = \Gamma(\{Y_s\}),$$

where Γ is homogeneous of degree one, concave, and increasing in all arguments, and Y_s is total output of sector s. The final good serves as the numéraire.

Structures and ICT Capital. Buildings in location r are produced locally in a sector-specific competitive construction sector, by combining units of the final good, $X_{r,s}$, and units of land, $O_{r,s}$, according to:

$$B_{r,s} = X_{r,s}^{1-\zeta_s} O_{r,s}^{\zeta_s}.$$

Each location r has a fixed supply of land zoned for production in sector s, denoted by $\bar{O}_{r,s}$. The same location-less capitalists that own the firms also own all the land.

A representative firm transforms the final output into ICT capital at a constant rate of u_K units of the capital good per unit of the final good.

Preferences. Workers of skill type e in location r and sector s supply their labor inelastically at a competitive wage $w^e_{r,s}$. They spend all their income on the consumption of the final good. Worker i also receives an idiosyncratic utility from living in location r, η^i_r, and from working in sector s in location r, $\xi^i_{r,s}$. Workers learns their location utility first, and their sector utility only after having chosen a location and before choosing a sector of employment within that location. The expected indirect utility of a type e worker before learning the realization of his preference shocks is

$$\bar{v}^e = \mathbb{E}_\eta[\max_r\{\eta^i_r \times \mathbb{E}_\xi[\max_s\{w^e_{r,s} \times \xi^i_{r,s}\}]\}]. \tag{3}$$

The location-less capitalists earn income from the dividends of their portfolio of all the firms in the economy and rents from their endowment of landholdings $\{\bar{O}_{r,s}\}$. Capitalists choose how many firms to create, and spend their net income on the freely traded final good.

Aggregation and General Equilibrium. For a given level of output, y_f, a firm's optimal choices of high- and low-skill labor, h_f and l_f, satisfy the following first order condition:

$$\log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\log\left(\frac{h_f}{l_f}\right) + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\log(y_f) + \frac{1}{\sigma}\log\left(\frac{\alpha^H_{r,s}}{\alpha^L_{r,s}}\right). \tag{4}$$

Equation (4) relates the marginal products of high- and low-skill labor to input quantities. As in the homothetic CES case, the parameter σ governs the elasticity of substitution between the different types of labor. However, the relative marginal product also depends on the scale of output, y_f. In particular, if $\epsilon_H > \epsilon_L$, high-skill labor is more complementary with scale, and, for given factor prices, the firm intensifies its use of high- relative to low-skill labor at higher levels of output.

Conditional on paying the fixed cost C to invest in ICT capital, firm f's choice of ICT capital, k_f, satisfies the following first order condition:

$$k_f + k_f^{\beta} = (p^K)^{-1} h_f \left(w^H_{r,s} + w^L_{r,s} \left(\frac{w^H_{r,s}}{w^L_{r,s}}\right)^{\sigma} y_f^{\frac{\epsilon^L - \epsilon^H}{\gamma}} \frac{\alpha^L_{r,s}}{\alpha^H_{r,s}} \right) \frac{(1-\gamma)\beta}{\gamma}, \tag{5}$$

where the optimal choice of ICT capital is increasing in the amount of high-skill workers at the firm, and falling in the unit price of capital.

We now introduce a set of policy functions that map firm productivity and location characteristics into input choices. Since these mappings are the same for all firms with the same efficiency z_f, we suppress firm subscripts and index firms by their efficiency. The function $y^{\cancel{I}}_{r,s}(z, h, \{w^e_{r,s}\})$ denotes the firm's output if it does not adopt ICT, incorporating the optimal choice of low-skill labor from equation (4), denoted $l^*_{r,s}(y, h, \{w^e_{r,s}\})$. Similarly, the function $y^I_{r,s}(z, h, \{w^e_{r,s}\}, p^K)$ denotes the output of a firm that adopts ICT capital, where optimal capital investment is taken from equation (5), denoted $k^*_{r,s}(y, h, \{w^e_{r,s}\}, p^K)$.

The problem of a firm is then to decide whether or not to pay the fixed costs for ICT investments, C, and to choose how many high-skill workers, h, to hire given its technology choice. We can write the profits of a firm with productivity z as follows:

$$\begin{aligned} \pi^*_{r,s}(z) = \max \Big\{ & \max_h \; p_s y^{\cancel{I}}_{r,s}(z, h, \{w^e_{r,s}\}) - w^H_r h - w^L_r l^*_{r,s}(h, y^{\cancel{I}}, \{w^e_{r,s}\}), \\ & \max_h p_s y^I_{r,s}(z, h, \{w^e_{r,s}\}, p^K) - w^H_r h \\ & - w^L_r l^*_{r,s}(h, y^I, \{w^e_{r,s}\}) - p^K k^*_{r,s}(h, y^I, \{w^e_{r,s}\}, p^K) - C \Big\}. \end{aligned} \tag{6}$$

The resulting optimal policies of a firm, $h^*_{r,s}(z)$ and $y^*_{r,s}(z)$, are functions of local prices and fundamentals.

For given factor prices, the solution to the investment problem is characterized by a cutoff rule in firm productivity: all firms in location r with fundamental productivity above a threshold value $z^*_{r,s}(\{w^e_{r,s}\}, p^K)$ adopt ICT capital. As a result, *average firm productivity* in location r and sector s, denoted $\bar{Z}_{r,s}$, satisfies:

$$\bar{Z}_{r,s} = \int_0^{\infty} z dG(z) + \int_{z^*_{r,s}(\{w^e_{r,s}\}, p^K)}^{\infty} z k^*(y^*_{r,s}(z), h^*_{r,s}(z), \{w^e_{r,s}\}, p^K)^{\beta} dG(z). \tag{7}$$

Average firm productivity in location r consists of two additive components. The first is the average efficiency of all firms in the location.[27] The second is an endogenous productivity component, resulting from the ICT adoption decisions of local firms. Both the ICT adoption cutoff for firm efficiency, z^*, and the amount of ICT capital, k^*, each firm purchases depend on local factor prices and location fundamentals.

[27]Since firms buy a building before drawing their efficiency, there is no selection on entry. There are no fixed costs of operation, so all firms produce some output. Our formulation abstracts from selection on firm efficiency at entry to focus on ICT adoption once a firm is active, in line with Combes, Duranton, Gobillon, Puga, and Roux (2012) who find no evidence of selection across cities of different sizes. The location-less capitalists pay all entry costs.

The fixed availability of land $\bar{O}_{r,s}$ for the production of commercial buildings leads to an upward-sloping supply curve for buildings in each location and sector. As a result, the price for a building, $p^B_{r,s}$, rises with the equilibrium number of firms in each location r and sector s. The location-less capitalists create new firms until expected profit is equal to local building costs. The equilibrium number of firms in a location and sector, $N_{r,s}$, satisfies the free entry condition,

$$\tau(N_{r,s}/O_{r,s})^{\frac{\zeta_s}{1-\zeta_s}} = \int_0^\infty \pi^*_{r,s}(z)dG(z), \tag{8}$$

where τ is a combination of model parameters. The parameter ζ_s controls the elasticity of building supply to building prices in a location and sector.

To simplify aggregation across workers, we make a distributional assumption on their idiosyncratic preferences for locations and sectors. Worker i of education type e draws their idiosyncratic preference shock for each location r from a Fréchet distribution with inverse scale parameter A^e_r and shape parameter κ^e. After making a location choice, workers draw a preference shock for each sector s from a Fréchet distribution with inverse scale parameter $D^e_{r,s}$ and shape parameter ϱ^e.

These assumptions yield expressions for the fraction of agents choosing to live in location r and for the fraction of workers choosing to work in sector s, conditional on moving into a location r:

$$\mathrm{P}^e(r) = \frac{A^e_r(\bar{v}^e_r)^{\kappa^e}}{\sum_r A^e_r(\bar{v}^e_r)^{\kappa^e}} \qquad \text{and} \qquad \mathrm{P}^e(s \mid r) = \frac{D^e_{r,s}(w^e_{r,s})^{\varrho^e}}{\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e}}, \tag{9}$$

where A^e_r plays the role of a location- and type-specific amenity term. Similarly, $D^e_{r,s}$ acts as a sector- and type-specific amenity term that is normalized within each region. The expected indirect utility of a worker of type e in location r before learning their sector specific preference shock, $\bar{v}^e_r$ has the following analytic expression:

$$\bar{v}^e_r = \hat{\gamma}^e \left(\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e} \right)^{\frac{1}{\varrho^e}}.$$

We denote the equilibrium quantities of high- and low-skill labor in region r and sector s by $H_{r,s}$ and $L_{r,s}$, respectively.[28]

The national final goods producer's demand for each sectoral input satisfies the following first order condition:

$$\frac{\partial\Gamma(\{Y_s\})}{\partial Y_s} - p^s = 0, \tag{10}$$

where p^s is the price of the sector s output. We denote the resulting demand functions by $Y^*_s(p^s, \{Y_{s'\neq s}\})$.

[28]We present the derivations of these expression in the Online Appendix. We define $\hat{\gamma}^e \equiv g\left(1 - \frac{1}{\varrho^e}\right)$ and $g(\cdot)$ is the gamma function.

Definition (Competitive Equilibrium)**.** *An equilibrium is a set of wages and worker allocations for each location, sector, and skill type,* $\{w^e_{r,s}, H_{r,s}, L_{r,s}\}$*, a location- and sector-specific price of land and allocation of land,* $\{p^O_{r,s}, O_{r,s}\}$*, a location- and sector-specific price and allocation of commercial buildings* $\{p^B_{r,s}, B_{r,s}\}$ *, a price and allocation of total capital* $\{p^K, K\}$*, a price for each sectoral good* $\{p^s\}$ *and quantities of sectoral output* $\{Y_s\}$*, an allocation of the final good to building production* $X_{r,s}$*, and a number of firms in each location* $N_{r,s}$*, such that*

(i) Firms in each sector make optimal labor, capital and technology adoption decisions according to equations (4), (5), and (6)

(ii) Consumers maximize their utility by choosing their location and sector, with choice probabilities given in equation (9)

(iii) Labor markets clear in each location for total high-skill labor $H_{r,s}$*,*

$$H_{r,s} = \frac{A^H_r(\bar{v}^H_r)^{\kappa^H}}{\sum_r A^H_r(\bar{v}^H_r)^{\kappa^H}} \frac{D^H_{r,s}(w^H_{r,s})^{\varrho^H}}{\sum_s D^H_{r,s}(w^H_{r,s})^{\varrho^H}} \bar{H} = N_{r,s} \int_0^\infty h^*_{r,s}(z)dG(z),$$

for all $s = 1, ..., S$*, and similarly for low-skill labor* $L_{r,s}$*.*

(iv) Land rental markets clear in each location:

$$(B_{r,s}/X^{1-\zeta_s}_{r,s})^{1/\zeta_s} = \bar{O}_{r,s}.$$

(v) Markets for commercial buildings clear in each location:

$$N_{r,s} = B_{r,s}.$$

(vi) The capital and final good markets clear nationally:

$$\Gamma(\{Y_s\}) = \sum_r \sum_s \Bigg(N_{r,s} \int_{z^*_{r,s}}^\infty k^*_{r,s}(z)dG(z)/u^K + X_{r,s} + CN_{r,s}(1 - G(z^*_{r,s})) \\ + w^H_{r,s}H_{r,s} + w^L_{r,s}L_{r,s} + (N_{r,s} \int_0^\infty \pi^*_{r,s}(z)dG(z) - p^B B_{r,s}) + p^O_{r,s}O_{r,s} \Bigg).$$

(vii) The markets for sectoral intermediate goods clear nationally:

$$Y^*_s(p^s, \{Y_{s' \neq s}\}) = \sum_r N_{r,s} \int_0^\infty y^*_{r,s}(z)dG(z).$$

(viii) The number of firms in each location is consistent with free entry in equation (8).

3.3 The Mechanism in a Simplified Version of the Model

Before taking the model to the data, we first consider a simplified version to illustrate its core mechanism: a declining national price of ICT capital interacts with constant location fundamentals to generate unbalanced labor demand growth across locations.

Suppose there is only one worker type e and one sector s so that we can suppress all sector and type indexing. As a result, the cutoff efficiency for ICT investments, z_r^*, has a simple analytical expression:

$$z_r^* = (p^K)^{\beta} \tilde{C} \, (w_r/\alpha_r)^{\frac{\gamma}{1-\gamma}}, \tag{11}$$

where $\tilde{C}$ is a combination of model parameters and the entry cost C. Equation (11) shows that the cutoff is lower the lower the price of ICT capital p^K. It is also increasing in the *adjusted* wage of location r, w_r/α_r.

Average firm-level productivity in location r can be expressed as

$$\bar{Z}_r = \int_0^{\infty} z dG(z) + \left(\hat{\gamma}\beta \, (w_r/\alpha_r)^{\frac{\gamma}{\gamma-1}} \, (p^K)^{-1}\right)^{\frac{\beta}{1-\beta}} \int_{z_r^*}^{\infty} z^{\frac{1}{1-\beta}} dG(z), \tag{12}$$

where $\tilde{\gamma}$ is a combination of model constants. The first component is the average efficiency of all firms in a location, which does not differ across locations. The second reflects the ICT adoption decisions of local firms, which depend on location r's fundamentals.

We now show first that locations with a lower adoption threshold experience faster average productivity growth as the price of ICT capital declines. In a second step, we show that the initial adoption threshold is lower in locations with higher location productivity, α_r. In a third step, we show the conditions under which the uneven growth of average firm productivity translates into urban-biased wage growth, such that growth occurs faster in *larger* places.

Productivity Growth and Adoption Threshold. In general, the effect of a decline in the ICT price on average local productivity depends on the shape of the productivity distribution $G(z)$.[29] If $G(z)$ is Pareto with shape $\vartheta > 1/(1-\beta)$ and minimum z_{min}, the response of average firm productivity in location r to a change in the price of ICT capital, holding local wages constant, is given by:

$$d\log(\bar{Z}_r) = -\frac{\bar{Z}_r - Z_0}{\bar{Z}_r}\Bigg(\underbrace{\frac{\beta}{1-\beta} d\log\left(p^K\right)}_{\text{direct effect}} + \underbrace{(\vartheta - \frac{1}{1-\beta}) d\log(z_r^*)}_{\text{indirect effect}}\Bigg),$$

whenever $z_r^* > z_{min}$ holds and where $Z_0 \equiv \int_0^{\infty} z dG(z)$ is average firm efficiency. It follows from equation (11), that the change in the firm efficiency cutoff for ICT adoption, $d\log(z_r^*)$, is proportional to the change in the ICT price, $d\log\left(p^K\right)$. By implication, aver-

[29]For general firm efficiency distributions, the change in average local productivity can be written:

$$d\log(\bar{Z}_r) = -\frac{\bar{Z}_r - Z_0}{\bar{Z}_r}\Bigg(\underbrace{\frac{\beta}{1-\beta} d\log\left(p^K\right)}_{\text{direct effect}} + \underbrace{(z_r^*)^{\frac{2-\beta}{1-\beta}} \frac{dG}{dz}(z_r^*)(\int_{z_r^*}^{\infty} z^{\frac{1}{1-\beta}} dG(z))^{-1}) d\log(z_r^*))}_{\text{indirect effect}}\Bigg).$$

Even in this generality, the direct effect is always larger in places that have a lower adoption threshold, i.e., places where $(\bar{Z}_r - Z_0)/\bar{Z}_r$ is higher. The presence of more firms above the adoption threshold implies a greater increase in total capital investment.

age firm productivity, $\bar{Z}_r$, rises fastest in locations with lower adoption thresholds, and higher average output per worker as p^K falls.

A decline in the ICT capital price, p^K, has two effects on average firm productivity in a location. First, there is a *direct effect* on capital adoption for firms above the threshold z_r^*, who adopt more capital at a lower price p^K. Second, there is an *indirect effect* through changes in the adoption threshold that implies that more firms find it profitable to pay the fixed cost to adopt the technology.

Adoption Threshold and Local Productivity. We now show that the adoption threshold in equation (11) is lower in locations with higher location productivity, α_r. This is not immediate since locations with higher α_r are also likely to pay higher wages. The key insight is that the adoption decision depends only on the *adjusted* wage the firm must pay to hire workers, i.e., w_r/α_r. This adjusted wage decreases in local productivity α_r in equilibrium.

To show this, we equate labor demand and labor supply to write the labor market clearing condition as:

$$N_r \bar{Z}_r \left(\gamma \alpha_r / w_r\right)^{\frac{1}{1-\gamma}} = \alpha_r^{1+\kappa} A_r (\alpha_r / w_r)^{-\kappa} \mathcal{G}, \tag{13}$$

where $\mathcal{G}$ is a general equilibrium constant that is equal across locations. Equation (12) shows that the average firm productivity $\bar{Z}_r$ is only a function of the *adjusted* wage. The free entry condition in equation (8) shows the same for the number of firms, N_r.

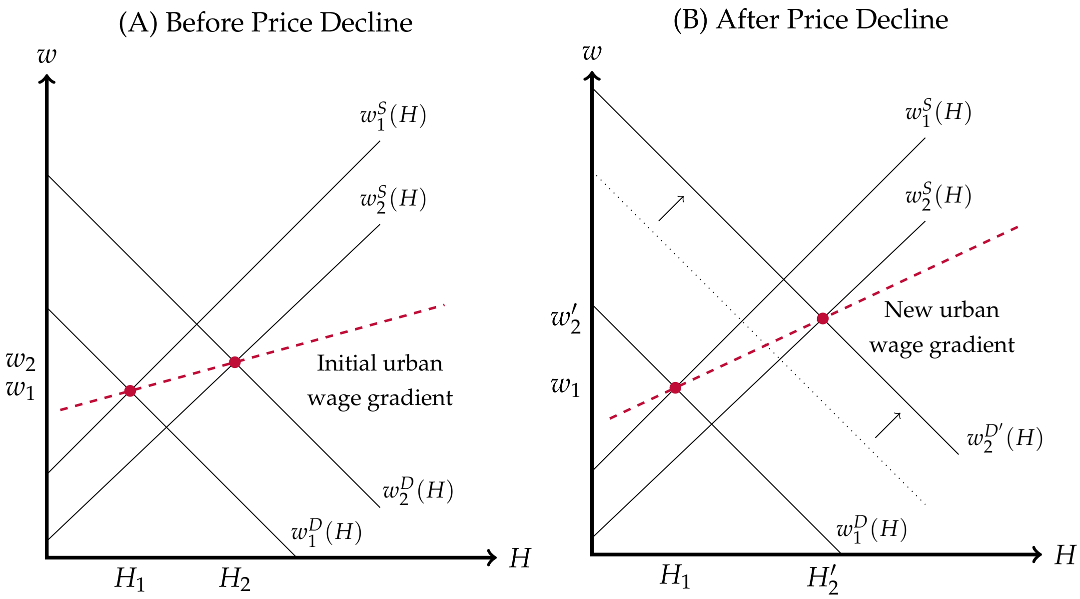
Now consider equation (13). Its left hand side can be shown to be a strictly increasing one-to-one function of the adjusted wage on $\mathbb{R}_+$, while its right hand side is a strictly decreasing one-to-one function of the adjusted wage on the same domain. As a result, equation (13) uniquely determines the adjusted wages w_r/α_r in all locations, with the general equilibrium constant $\mathcal{G}$ determined by the constraint on total labor supply.

It is then straightforward to see that for given amenities A_r, the equilibrium adjusted wage is a decreasing function of local productivity α_r which appears by itself on the right hand side of equation (13). By implication, locations with a higher location productivity have lower adjusted wages and lower adoption thresholds. Since, as discussed above, average firm productivity increases more as the price falls in locations with a lower adoption threshold, locations with a higher location productivity also see faster average firm productivity growth, and hence faster labor demand growth (see the left hand side of equation (13)).

Productivity Growth and Urban-Biased Wage Growth. Finally, we discuss under what circumstances biased labor demand growth translates into economic growth that is biased towards *larger* locations, or equivalently a steepening of the equilibrium urban wage gradient.

Consider a version of our simplified model with only two locations, 1 and 2. The left panel of Figure 7 shows the determination of the (log) urban wage gradient in this econ-

FIGURE 7: URBAN-BIASED WAGE GROWTH IN EQUILIBRIUM



Notes: The left panel of this figure shows the labor market equilibrium in the model with two locations, with log employment H on the x-axis and log wages w on the y axis. The (log) urban wage gradient is the locus of the equilibrium points. The right panel shows how the equilibrium changes when the second location receives an increase in labor demand. There is an adjustment to the general equilibrium constant $\mathcal{G}$ which we do not show, since it shifts both labor supply functions downwards by the same amount.

omy. It depicts the (inverse) labor demand and supply curves from the left and right hand side of equation (13), respectively.

Suppose location 2 has both higher amenities A_r and higher fundamental productivity, α_r. As a result, both the labor supply curve and labor demand curve are shifted to the right relative to location 1. The line connecting the two equilibrium points represents the gradient of wages with respect to employment; the urban wage gradient in this context. Its slope is always bounded between the slopes of the labor supply and demand curves, which are the same in both locations.

We showed above that a decline in the price of ICT capital leads to a greater increase in labor demand in the location with higher location productivity, α_r, in this case location 2. The right panel of Figure 7 shows the same economy as the left panel after a decline in the ICT price. In this new equilibrium, the gradient of wages with respect to employment increases. The fact that local amenities and location productivity are positively correlated is important for this result. Had this correlation been negative, i.e., had region 2 had lower amenities while also having higher location productivity, then the higher location productivity would still imply a shift of the labor demand curve through investment as the price of ICT capital falls. However, this investment would now *flatten* the urban wage gradient.

Had the initial wage gradient had been just a result of location productivity differences (with no amenity shifters across locations), the urban wage gradient would remain unchanged (and would be equal to the labor supply elasticity). So the steepening of the gradient over time in the data suggests that the initial urban wage gradient was the result of an interaction between amenity and location productivity differences. In particular, to generate the urban-biased wage growth in the data, locations with greater population density must have higher local amenities, A_r, and greater location productivity, α_r, on average.

In general, the urban wage gradient increases as p^K declines as long as there is a positive correlation between α_r and A_r. The Online Appendix contains a formal treatment of this claim for the general case of R regions.

4. Quantitative Analysis

We now assess the quantitative importance of our mechanism in explaining the new urban bias in economic growth. We choose the parameters of the full model to match central features of the U.S. economy in 1980 and then trace out the equilibrium response of the model to the observed decline in the ICT price between 1980 and 2015.[30] Table 1 summarizes our parameter estimates.

4.1 Parameter Calibration

For our quantitative exercise, we map locations r in the model to commuting zones in the data. We focus on two "sectors" s, SSS and all other industries (Non-SSS). We define workers with at least a college degree as high-skill ($e = H$) and all others as low-skill ($e = L$).

Production Function Parameters: $\sigma, \epsilon, \gamma, \rho$. To calibrate the elasticity of substitution between inputs, σ, and the composite scale parameter $(\epsilon^H - \epsilon^L)/(\gamma\sigma)$ we use the firm's first order condition for inputs in equation (4). Integrating this equation over the firm efficiency distribution, $G(z)$, within location r and sector s and taking first differences yields a structural equation of the form

$$(14) \qquad \Delta \log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\mathbb{E}_z\left[\Delta \log\left(\frac{h^*_{r,s}(z)}{l^*_{r,s}(z)}\right)\right] + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\mathbb{E}_z\left[\Delta \log\left(y^*_{r,s}(z)\right)\right] + \nu^Y_{s,r},$$

where $\nu^Y_{s,r} \equiv \frac{1}{\sigma}\Delta \log\left(\alpha^H_{r,s}/\alpha^L_{r,s}\right)$ is an unobserved error and where we have suppressed the dependence on local prices in the policy functions, $h^*_{r,s}(z)$, $l^*_{r,s}(z)$, and $y^*_{r,s}(z)$.

We calibrate the production function parameters by interpreting the model as the true data generating process. We take the data as the outcome of general equilibrium changes in ICT capital adoption caused by the secular decline in its price observed in the data. In our calibration, we restrict changes in the location fundamentals, $\{\alpha^e_{r,s}, A^e_r, D^e_{r,s}\}$, to be orthogonal to the systematic wage growth patterns induced by the decline in the ICT price.

[30] We outline our computational algorithm for solving for the equilibrium in the Online Appendix.

Since we lack firm level data, we proxy the average local changes in the firm level skill ratio with regional aggregates.[31] Similarly, we proxy average changes in firm level output with changes in regional GDP at the industry level within each commuting zone, leaving us with the equation

$$\text{(15)} \qquad \Delta \log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\left[\Delta \log\left(\frac{H_{r,s}}{L_{r,s}}\right)\right] + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\left[\Delta \log\left(\frac{Y_{r,s}}{N_{r,s}}\right)\right] + \nu^Y_{s,r}.$$

For two reasons, we cannot simply run the regression in equation (15) across commuting zones in the data to recover the production function parameters. First, $H_{r,s}$ and $L_{r,s}$ are simultaneously determined with wages via the labor supply functions in equation (9). Second, in the model the unobserved error term $\nu^Y_{r,s}$ in equation (14) is correlated with firms' input choices.

As a result, we calibrate the parameters by running an IV regression that is valid in the world of the model. We instrument for changes in the skill ratio in region r using the change of the sector-specific skill ratio in all other regions, $r' \neq r$, multiplied by its initial skill ratio. We instrument for the change in local-sectoral GDP with the leave-one-out growth rate in local sectoral payroll.[32] The orthogonality restriction within the model is that the initial levels of the unobserved local productivity ratio $\alpha^H_{r,s}/\alpha^L_{r,s}$ and amenities $\{A^e_r, D^e_{r,s}\}$ are uncorrelated with their subsequent changes.

Table A.5 presents the results from estimating equation (14) across commuting zones with at least 50,000 workers between 2000 and 2015.[33] We estimate the elasticity of substitution, σ, to be 3.3 and the composite parameter $(\epsilon^H - \epsilon^L)/\gamma\sigma$ to be 0.55.[34] Since the scale elasticity difference, $\epsilon^H - \epsilon^L$, is not separately identified from production data, we normalize $\epsilon^H = 0$ and choose γ to match the 1980 labor share. The implied value for the low skill scale elasticity, ϵ^L, is -1.1.

Labor Supply Elasticities: ϱ^e, κ^e. There are four labor supply elasticities in the model: one across commuting zones and one across sectors, for each of the two skill groups.

To calibrate the sectoral elasticities, ϱ^e, we use the sectoral choice probabilities in equation (9) and take logarithms and time differences to obtain:

$$\text{(16)} \qquad \Delta \log\left(\frac{P^e\left(\text{SSS} \mid r\right)}{P^e\left(\text{Non-SSS} \mid r\right)}\right) = \varrho \Delta \log\left(\frac{w^e_{r,\text{SSS}}}{w^e_{r,\text{Non-SSS}}}\right) + \psi^e_r,$$

where $\psi^e_r \equiv \Delta \log\left(D^e_{r,\text{SSS}}/D^e_{r,\text{Non-SSS}}\right)$ is a structural residual, and we pool data across

[31] More detail, along with a discussion of the potential biases these proxies introduce is provided in Appendix C.

[32] Payroll is a fundamental component of value added measures and better measured than the GDP growth rate. The documentation of the local industry GDP numbers by BEA does not contain much detail. The principal component of their measure of a sector's regional GDP is its payroll that is sourced from administrative data records.

[33] We use GDP data from 2001 for 2000, as that is the first year local GDP data was released by the BEA. We also include time-sector fixed effects.

[34] While the elasticity of substitution is higher than previous estimates in the literature, the inclusion of non-homothetic scale elasticities means that our estimate cannot be directly compared.

skill groups. In the model, unobserved changes in these sectoral amenities are correlated with equilibrium changes in wages through the optimal choices of workers. As such, we calibrate the sectoral elasticites ρ^e by running an IV regression in which we instrument the change in a region's wage ratio with its initial wage ratio times the average growth rate of the ratio in all other regions.

Table A.6 in the Appendix presents the results from this estimation on the Census data for each decade from 1980 to 2010 using commuting zones with at least 50,000 workers. Our preferred specification (Column 4) yields a sectoral labor supply elasticity for high-skill workers, ϱ^H, of 1.45, and for low skill workers, ϱ^L, of 1.69.

For the spatial labor elasticities, κ^H and κ^L, we use estimates from Diamond (2016), who finds that college educated workers are more responsive to spatial wage differentials, with $\kappa^H = 4.98$ and $\kappa^L = 3.26$.

Finally, we assume a constant elasticity of substitution final good aggregator, $\Gamma(\cdot)$, with elasticity ρ which we calibrate to match the change in the aggregate SSS share in national payroll when varying the ICT price between its 1980 and 2015 values.[35]

Technology Adoption Parameters: β, μ_s, C, u_K. We choose β so that the model matches the change in the aggregate ICT capital stock in SSS between 1980 and 2015 (see Figure A.13) when we change the ICT price to its 2015 value leaving all other parameters at their values from the 1980 calibration.[36] Second, we choose C such that 5% of SSS firms in 1980 have adopted ICT.[37] For simplicity, we assume only SSS makes use of ICT capital, so that $\mu_{NSSS} = 0$ and $\mu_{SSS} = 1$.[38] The level of the productivity of ICT capital production, u_K, is not separately identified from the fixed cost C and we normalize it to 1 in 1980.

Firm Productivity Distribution: ϑ. Following a long literature documenting the good fit of the Pareto distribution in describing the U.S. firm size distribution, we assume $G(z)$ follows a Pareto distribution with a scale parameter of 1 and shape parameter of ϑ. In the model, the shape parameter ϑ governs the mean and tail behaviour of the firm size distribution. Since our model has only single-establishment firms, we use data on establishments, and set $\vartheta = 2$ to reproduce the tail behaviour of the establishment distribution in the U.S. Census.[39]

[35] In a robustness exercise in the Online Appendix, we assume that sectoral prices are invariant to changes in productivity (effectively assuming that SSS and Non-SSS are perfect substitutes in producing final output).

[36] The ICT equipment price times series comes from the NIPA Table 5.3.4. In the NIPA data we take the ratio of ICT capital stock to value added at the sector level, and match the change in this ratio between 1980 and 2015 for the SSS sector.

[37] Bessen (2017) documents the fixed cost nature of many ICT investments in the U.S. economy.

[38] The very low adoption of ICT technologies in Non-SSS sectors relative to SSS sectors in both 1980 and 2015 provides suggestive evidence that these technologies are differently productive across sectors. Autor et al. (2003) document that ICT "complements workers in performing non-routine problem-solving and complex communications tasks." Occupations that carry out such tasks are disproportionately found in the SSS industries, suggesting that ICT technology leads to much great productivity gains in these industries compared to others.

[39] Axtell (2001) finds that $\vartheta \approx 1$ for firms. Given that our data from the CBP is at the establishment level, and the establishment size distribution is has a thinner tail than the firm size distribution, we employ a shape parameter of 2. We have experimented with different values of this parameter and find little quantitative difference in our results.

TABLE 1: Overview of Model Parameterization

	Description	Value	Source/Target
Parameter			
γ	Decreasing Returns to Labor Inputs	0.61	1980 Aggregate Labor Share
σ	Elasticity of Substitution btw High- and Low-Skill Labor	3.3	Equation (14)
ϵ^L	Low-Skill Scale Elasticity	-1.1	Equation (14)
ϵ^H	High-Skill Scale Elasticity	0	Normalisation
β	ICT Capital Elasticity	0.62	Match Aggregate ICT Investment 1980-2015
μ_s	ICT Capital Productivity	(1,0)	See text
C	Fixed Cost of ICT Investment	20.9	Match level of ICT Capital 1980
ζ_s	Firm Supply Elasticity	(0.25,0.13)	Match spatial differences in avg. establishment size
τ_s	Entry Cost Level	(1.07,1.94)	Match average establishment size 1980
ϑ	Efficiency Shape Parameter	2	Tail of Establishment Sizes
κ^H	High-Skill Spatial Labor Supply Elasticity	4.98	Diamond (2016)
κ^L	Low-Skill Spatial Labor Supply Elasticity	3.26	Diamond (2016)
ϱ^H	High-Skill Sectoral Labor Supply Elasticity	1.45	Equation (16)
ϱ^L	Low-Skill Sectoral Labor Supply Elasticity	1.69	Equation (16)
ρ	Elasticity of Substitution between SSS and Non-SSS	3.6	Change in SSS Payroll Share
Location Fundamentals			
$\alpha^e_{r,s}$	Location Productivity	Various	1980 Sector-Region-Skill-Specific Wages
A^e_r	Location Amenities	Various	1980 Sector-Region-Skill-Specific Employment
$D^e_{r,s}$	Sectoral Amenities	Various	1980 Sector-Region-Skill-Specific Employment
u_K	Productivity of ICT Capital Production	Varying	BEA ICT Capital Equipment Data

Notes: This Table shows the baseline parameterization of the model. The location fundamentals vary across regions and by education group and sector, so their values are not listed. The productivity of ICT capital production, u_K, is the parameter we vary in counterfactuals. Table A.7 in the Appendix shows the values for the moments targeted in the estimation in model and data. Where two values appear for a parameter (representing the value for the two sectors), the value for SSS is first.

Housing and Capital Production: $\zeta_s, \bar{O}_{r,s}$. The parameter ζ_s governs the elasticity of the number of firms to local firm profitability. On average, larger commuting zones have higher wages in the data and hence higher location productivity, $\alpha^e_{r,s}$ in the model. As such, firms in these larger commuting zones will tend to be more profitable and so in equilibrium ζ_s shapes how average firm size changes with population size.

We choose ζ_s to match the slope coefficient of a univariate regression of average establishment size on regional employment, separately for SSS and Non-SSS industries (see Figure A.14 in the Appendix).[40] Moreover, we assume the amount of land zoned for each sector is the same across regions, i.e., $\bar{O}_{r,s} = \bar{O}_s$. We choose sectoral land supply, $\bar{O}_s$, to match the average establishment size in the aggregate economy for both sectors.[41]

Location Fundamentals: $\alpha^e_{r,s}, A^e_r, D^e_{r,s}$. We infer location fundamentals as structural residuals following the quantitative spatial economics literature (see Redding and Rossi-Hansberg (2017)). For the 1980 cross-section of data, we choose location productivity, $\alpha^e_{r,s}$, to match observed high- and low-skill labor demand in all regions and sectors given the observed wages $w^e_{r,s}$. Similarly, we infer the location and skill group specific amenity term, A^e_r, and the location, skill group and sector-specific amenities $D^e_{r,s}$ to match location choices of workers and sectoral employment shares exactly. We plot the local fundamental productivity terms against commuting zone employment in Figure A.15. SSS productivity for both the high and the low skill rises much more sharply with 1980 commuting zone employment; the model infers that large cities have a particular advantage in the production of SSS. Finally, we plot the correlation between the local amenity term A^e_r and the location productivity term, $\alpha^e_{r,s}$ (see Figure A.16). As in the discussion of Section 3.3, there is a strong correlation between inferred productivities in both sectors and inferred amenities, suggesting that a decline in the ICT price generates urban-biased growth in the model.

4.2 Findings

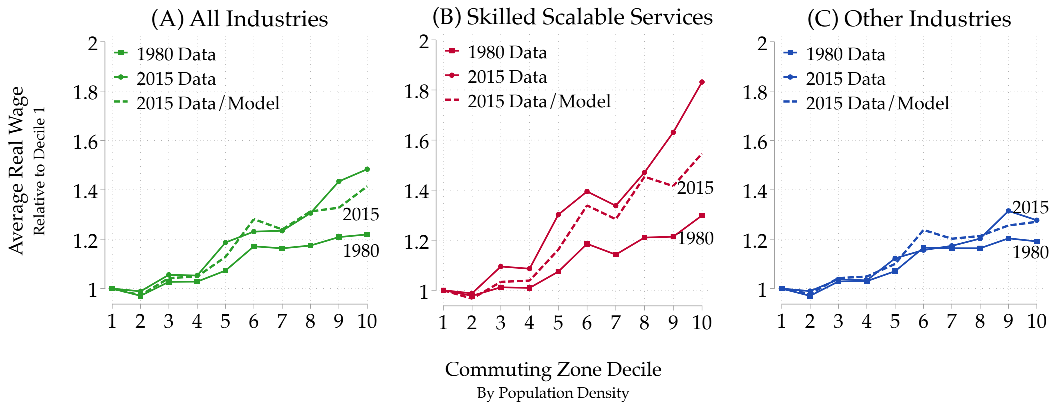
We now quantitatively assess the ability of our mechanism to explain the urban bias in recent U.S. wage growth. We take the model with location fundamentals calibrated to the 1980 data and vary the productivity of ICT capital production, u_K, to trace out the observed path of the ICT price in the BEA data between 1980 and 2015. We adjust the relative supply of high- and low-skill workers to match the data, and solve for the sequence of static equilibria implied by the price path, holding all other model parameters and regional fundamentals constant.

Figure 8 replicates Figure 1 from the introduction. It compares the wage growth across

[40] To measure average establishment size across space, we obtain total employment and the number of establishments for all U.S. commuting zones and industries in 1980 from the County Business Patterns data using the imputations provided by Eckert, Fort, Schott, and Yang (2019).

[41] Choosing land supply in this way does not imply that it is equally costly to build in all locations. Instead, places that have higher populations will have endogenously higher entry costs due to crowding out of available space, as governed by ζ_s. An alternative is to use an estimate of the elasticity of commercial buildings to population size, and then infer the land supply $\bar{O}_{r,s}$ as a structural residual.

FIGURE 8: THE NEW URBAN BIAS IN THE MODEL



Notes: This figure shows average wages across commuting zone groups, in the aggregate and by industry group, plotted relative to their level in the first group. The figure shows both wages in the data (solid lines) and in the model generated counterfactual data (dashed lines) for 2015. By construction, the data and the model wages are the same in 1980. In contrast to Figure 1, the underlying data used is the Decennial Census and the American Community Survey. To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density, each accounting for roughly one tenth of the U.S. population in 1980 The wage data is adjusted by the Bureau of Labor Statistics' CPI for urban consumers.

cities generated by the decline in ICT prices in our counterfactual exercise to the urban biased wage growth observed in the data.[42] In 1980, by construction, the model matches the data exactly. The ICT price decline observed in the data generates sizeable urban-biased wage growth in the model: the 2015 wage-density gradient in the model matches the data quite closely. The model explains about 84% of the urban bias in wage growth in the data.[43] The second and third panel of Figure 8 show that both in model and data the urban bias in average wage growth is driven by almost entirely by the SSS sector.

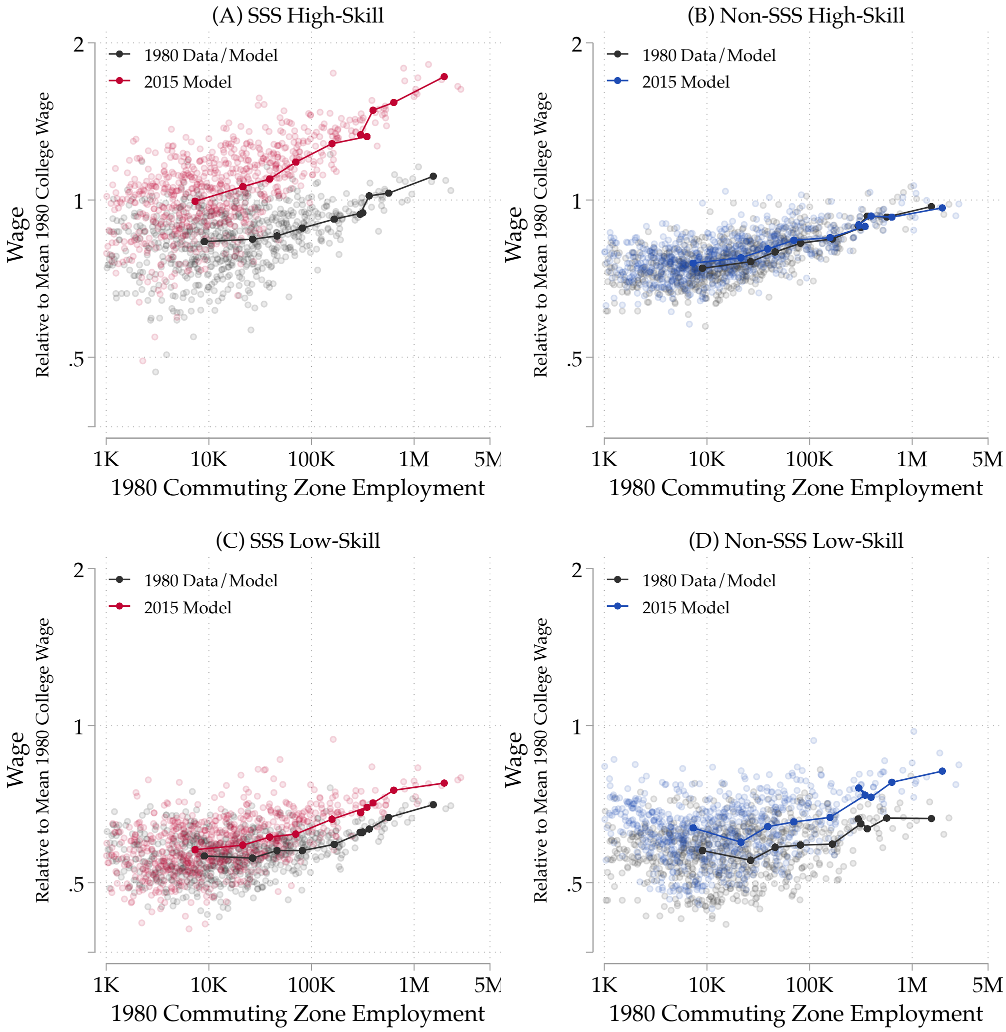
In Appendix B, we show that the decomposition of average wage growth into changes in within skill group wages and changes in the skill composition of the SSS sector looks similar in model and data. The labor supply function across sectors and space generates approximately correct changes in wages and quantities in response to the labor demand shock caused by the decline in the ICT price.

Now we discuss in more detail how the decline in the ICT price leads to urban-biased wage growth through the mechanism of Section 3. The direct impact of the price decline is to induce urban-biased ICT investments due to the underlying differences in the fundamental productivity of locations. As the ICT price declines, the ICT capital stock of SSS firms grows much faster in larger commuting zones, reflecting adoption both on the intensive and extensive margin (see Figure A.10 in the Appendix). These differences

[42] Figure 8 replicates Figure 1 from the introduction in the Census data we use to calibrate the model. We cannot use the LBD data for the calibration of the model since we require data on educational attainment of the labor force within each commuting zone, which is not available in the LBD. In the Online Appendix, we show that the wage growth trends in the LBD and in the U.S. Census are very similar.

[43] We compute this number by computing the fraction of tenth decile wage growth in the data replicated by the model in the leftmost panel of Figure 8.

FIGURE 9: WAGES IN THE MODEL IN 1980 AND 2015
ACROSS COMMUTING ZONES BY EDUCATION GROUP AND SECTOR



Notes: This figure plots commmuting zones wages against employment in the model-generated data in 1980 and 2015, by skill and industry group. "High-skill" is defined as workers with at least a college degree; all other workers are defined as "low-skill." Scatter dots are individual commuting zones, with black representing the 1980 data from the Population Census which is matched exactly in the model. Colored dots are the model predictions for each commuting zone in 2015. The connected dots are the averages within the ten density decile groups used throughout the paper, for both 1980 and 2015. To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density each accounting for roughly one tenth of the U.S. population in 1980.

in ICT investments translate into faster average firm-level productivity growth in larger commuting zones.

Figure 9 shows the response of wages within each skill group and sector across commuting zones.[44] The wage growth of SSS workers of both skill types exhibits a clear urban

[44]Since population density has no direct interpretation through the lens of the model, we present outcomes as a function of local employment instead. Nevertheless, since each commuting zone in the data is present in the model we can associate a population density with each commuting zone in the model and are still indicating averages within density deciles (see the dots in Figure 9).

bias, reflecting the faster adoption of ICT technologies and resulting productivity growth in larger (and denser) locations. Outside of SSS, no urban-biased wage growth occurs.

The non-homotheticity in firms' production functions is central to understanding differences across skill groups. High-skill workers see much more wage growth everywhere, and in particular in the largest locations, compared to low-skill workers. This reflects the different complementarities with scale for the two skill groups: all else equal, marginal products of the low-skill in SSS *fall* at the larger scales that ICT investment brings, and this partially offsets increased overall labor demand in general equilibrium. Low-skill wages grow on average by 15% in the sector, with a mild urban bias, broadly consistent with the patterns in Figure A.2. This is difficult to achieve in a homothetic model, like that of Krusell et al. (2000), which would generally imply far too much wage growth for low-skill workers. The Online Appendix discusses this issue in detail.

Non-SSS wages for low-skilled workers exhibit some growth, reflecting the fact that the relative price of the Non-SSS good rises with ICT investment in SSS. However, for the high-skilled in Non-SSS, this is counterbalanced by the fact that the overall population of skilled workers increases, which tends to put downward pressure on their wages. These patterns are at odds with the data, but we stress that our model is not a complete accounting for all patterns of wage growth since 1980. In particular, we have no general productivity growth in other sectors, and we are not accounting for other important determinants of low-skill wages, such as the disappearance of relatively highly-paid manufacturing jobs and their replacement with low-skill service jobs.

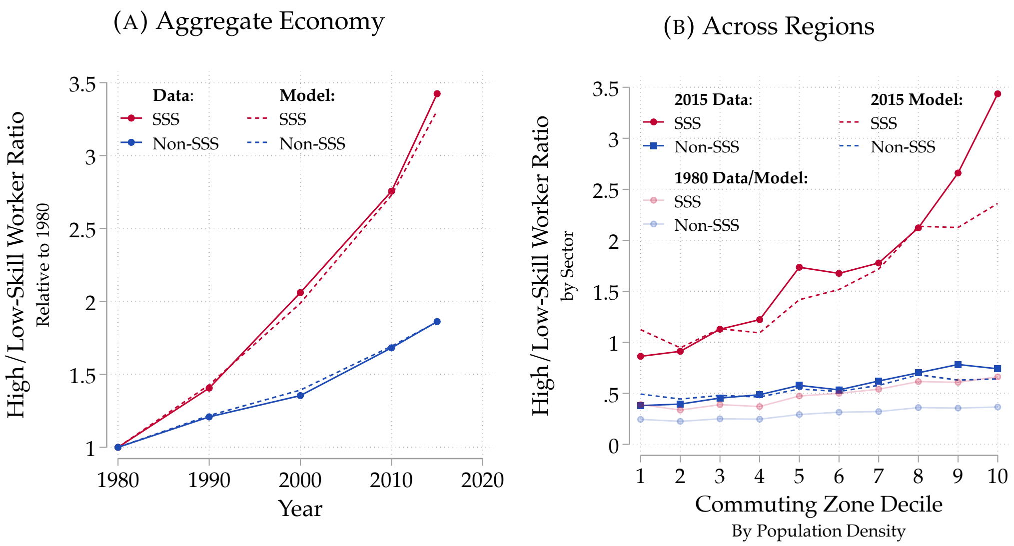
Overall, the decline in the ICT price generates labor demand that is biased towards skilled workers and larger commuting zones with higher population density. While part of this labor demand shock is reflected in wages, the upward sloping labor supply implies that some of it is reflected in compositional changes of the local workforce.

The right panel of Figure 10 shows the the ratio of high- to low-skill workers within each sector across commuting zones in 1980 and 2015 in model and data. As with average wages, the model matches these ratios within each commuting zone exactly in 1980. The model predicts the urban-biased skill deepening in SSS remarkably well. The fastest skill deepening occurs in the largest commuting zones, where firms adopt most ICT, and the non-homotheticity in their production functions tilts their labor demand towards more skilled workers.

However, the model does not generate the entire rise in the skill ratio for the densest commuting zones observed in the data; just as it did not reproduce the entirety of the SSS wage growth in these commmuting zones (see Figure 8). There are two reasons for this.

First, beyond ICT adoption, there could be other contemporaneous forces improving average firm productivity in the largest commuting zones in the same period. Second, we abstract from an endogenous amplification mechanism highlighted in the literature: agglomeration spillovers among high-skill workers. In a model with such spillovers, the urban biased increase in the high- to low-skill worker ratio would entail further produc-

FIGURE 10: SKILL DEEPENING IN MODEL AND DATA



Notes: The left panel of this figure shows the growth in the ratio of college-educated to non-college workers in both the model and Decennial Census data by year and sector. The high-skill group is mapped to workers with college degrees. The low-skill group is mapped to workers without college degrees. The right panel of this figure shows this ratio in 2015 in both model and data by sector across the commuting zone groups of increasing density used throughout the paper. To construct groups, we order commuting zones by their population density in 1980 and then split them into ten groups of increasing density each accounting for roughly one tenth of the U.S. population in 1980.

tivity gains in SSS (see, e.g., Giannone (2017) and Rossi-Hansberg et al. (2019)) generating additional wage growth and skill deepening compared to our model.

Finally, we turn to the aggregate implications of the ICT price decline through the lens of our model. While in calibrating the model we did not attempt to match the aggregate wage growth path of the U.S. economy, it generates realistic changes in *relative* wages and quantities across sectors. Figure A.8 in the Appendix shows the relative SSS to Non-SSS wage growth over time in model and data, while the left panel of Figure 10 shows the ratio of skilled to unskilled employment in SSS and Non-SSS in model and data.[45]

IMPLICATIONS

Recent economic growth has been strikingly biased towards the richest and largest cities in the U.S. This paper shows that understanding why requires a focus on a small set of skill- and information-intensive service industries, which we call Skilled Scalable Services. These services have been the key beneficiaries of innovation in ICT, and have used it to scale up their operations in the most productive U.S. cities. A better understanding of Skilled Scalable Services has the potential to unlock new perspectives on the nature of

[45]In our counterfactual exercises, we do adjust the fraction of the population with a college degree as in the data. However, the changing sectoral choice of high- and low-skill workers shown in Figure 10 are the sole result of the economic mechanisms in the model.

economic growth in knowledge economies, and the rising inequality between workers and regions that accompanies it.

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Appendix

A. Additional Figures and Tables

This section contains additional figures and tables.

A.1 Figures

Figure A.1 shows the average commuting zone wage in SSS and Non-SSS industries plotted against its population density in 1980 and 2015.

Figure A.2 plots average wage growth by skill level and sector, across the ten density decile bins used throughout the paper.

Figure A.3 shows employment shares across commuting zone groups in 1980 and 2015. Already in 1980, SSS industries are the only group of industries whose local employment share increase monotonically in commuting zone density. The average SSS employment share in the least dense group of commuting zone is about 13% in 1980, while it is more than 25% in the most dense commuting zones. In 2015 SSS employment shares in the densest commuting zones have decreased slightly.

Figure A.4 shows the urban bias in average employment shares is stronger for all of the SSS sub-industries individually than for any other industry in the U.S. economy. To construct the graph, we compute employment shares by industry for each 2-digit NAICS industries, then average across all Census years between 1980 and 2010 and the 2015 ACS. We then graph the employment share relative to the employment in the group of least dense commuting zones. This normalization highlights which industries have an unbalanced employment share across commuting zones ordered by population density.

Figures A.5 and A.6 show wage growth and ICT adoption for all 2-digit NAICS industries. They demonstrate that the four constituent 2-digit NAICS industries we refer to as SSS all broady exhibit the same patterns we documented in the main body of the paper.

Figure A.7 shows the urban-biased wage growth of certain occupations and education groups within and outside the SSS sector. We follow Jaimovich and Siu (2020) and Rossi-Hansberg et al. (2019), and define CNR occupations to include occupations with SOC-2 classifications 11 to 29 and Non-CNR occupations to include the remainder of SOC-2 classifications. The left panel shows that workers in cognitive-non-routine occupations within SSS have exhibited strongly urban-biased wage growth between 1980 and 2015, while those outside SSS have not. The same is true for workers not in these occupations: if they work in SSS there wage growth exhibited urban bias, if they worked outside SSS they did not. The right panel shows that workers with at least a college degree within SSS have seen strong urban-biased wage growth in recent decades, while those outside SSS have not. Similarly, non-college workers have seen urban-biased wage growth only for workers within SSS.

Figure A.8 shows average wages in SSS relative to average wages in Non-SSS industries since 1980, in both model and data. The model successfully traces out the SSS wage premium growth in the data since 1980. We also report growth of the SSS wage premium across commuting zones for completeness. Figure A.9 shows the growth in the SSS wage premium across commuting zones between 1980 and 2015 in data and model.

Figure A.10 shows the ICT capital stock at SSS firms across commuting zones in the model. We show these stocks for 1980, 1990, 2000, 2010, and 2015 each corresponding to a different value of the ICT price. As the price of ICT capital falls, SSS establishment in more dense locations disproportionately adopt ICT technology in the most dense cities.

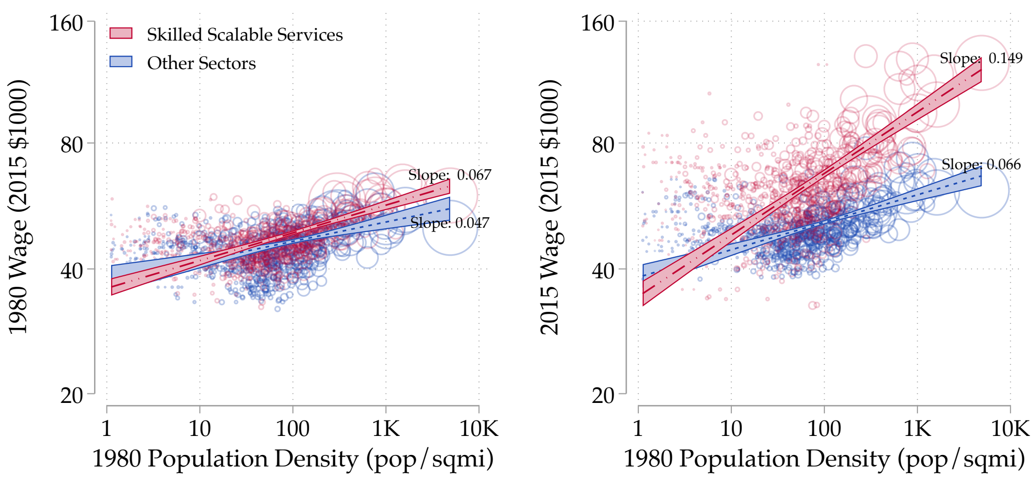
A.2 Tables

Table A.1 shows employment shares and real wages by skill group and and sector across our ten groups of commuting zones ordered by population density.

We also produce detailed statistics for the 25 largest commuting zones in tables A.2.

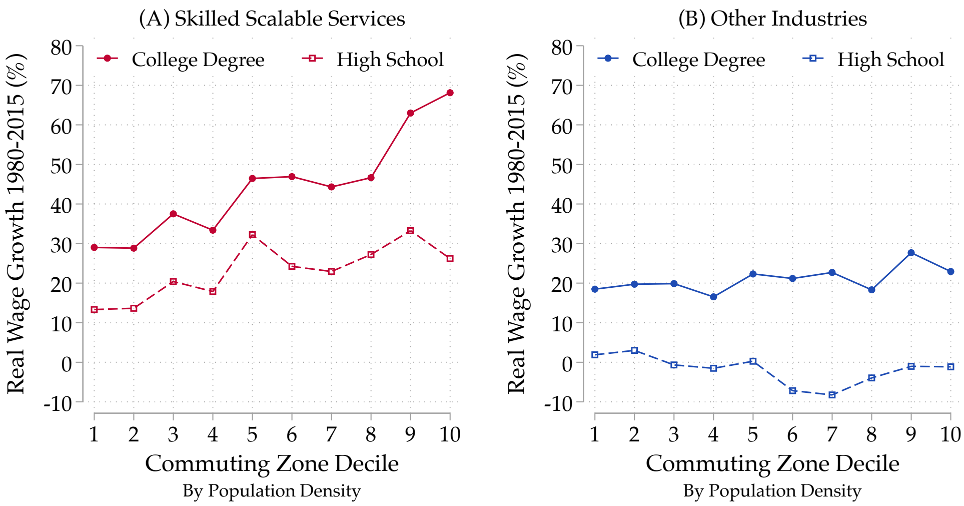
Table A.3 provides more detail on the urban bias of wage growth in occupation groups, education groups, and industries. We run separate regression for the growth of commuting-zone-level average wages of CNR workers in SSS and Non-SSS, and college-educated workers in SSS and Non-SSS on population density. The results are consistent throughout all specifications: SSS wage growth exhibits a stronger urban bias than wage growth for CNR workers or for college-educated workers. Wages of SSS workers not in CNR occupations and without college education exhibit a stronger urban bias than the wages of CNR workers or college educated workers in Non-SSS.

FIGURE A.1: AVERAGE WAGES
ACROSS COMMUTING ZONES BY SECTOR IN 1980 AND 2015



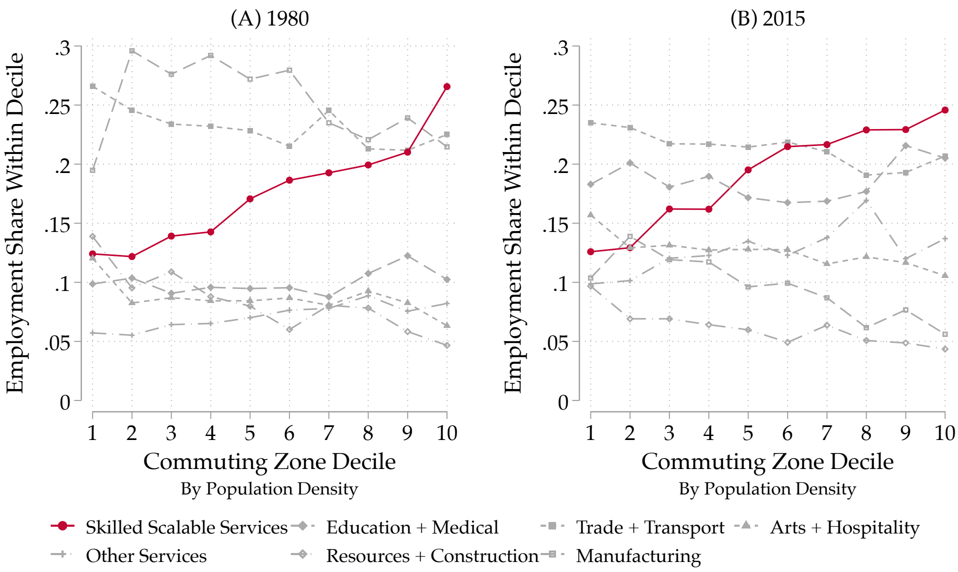
Notes: The left panel of this figure plots average wages at the commuting zone and sector level against commuting zone density in 1980. Size of circles is 1980 population. The right panel does the same for 2015. All wages are in 2015 dollars. Alaskan commuting zones and eight commuting zones under 1 person/sqmi are omitted. The data are from the Decennial Census (1980) and the ACS (2015). The data is adjusted by the BLS CPI-U.

FIGURE A.2: WAGE GROWTH BY SKILL GROUP ACROSS COMMUTING ZONES



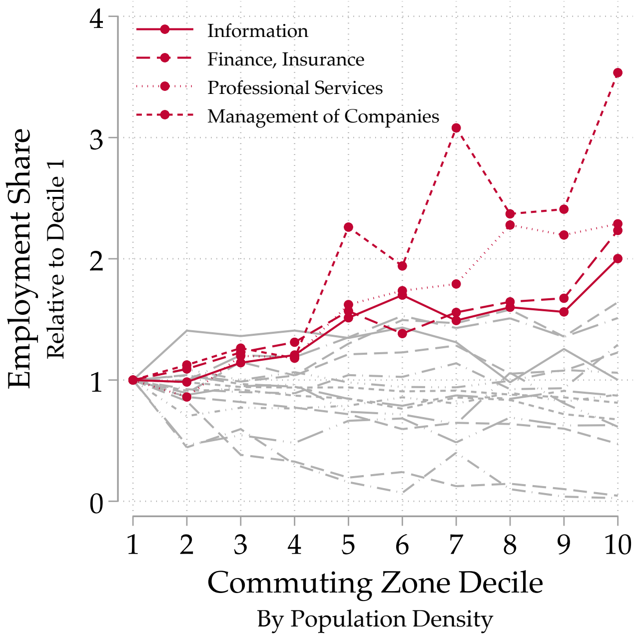
Notes: This figure plots average wage growth between 1980 and 2015 by the 10 commuting zone density deciles used throughout the paper. Panel (A) shows the SSS industries and Panel (B) shows all other industries. The data are from the Decennial Census (1980) and the ACS (2015), adjusted by the BLS CPI-U.

FIGURE A.3: SECTORAL EMPLOYMENT SHARES IN 1980 AND 2015 ACROSS COMMUTING ZONES BY INDUSTRY



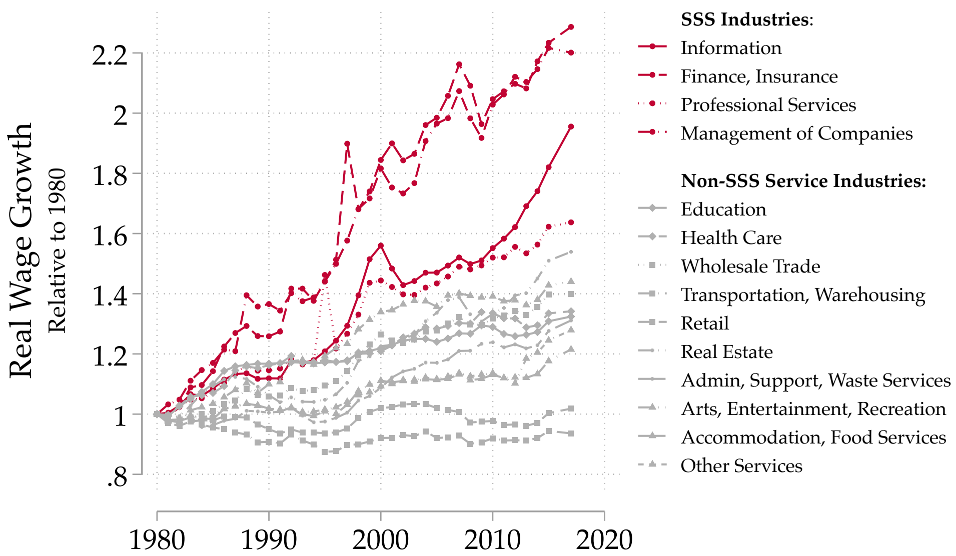
Notes: This figure plots employment shares in 1980 (Panel (a)) and 2015 (Panel (b)) for major industry groupings, by the ten density decile groups for commuting zones used throughout the paper. The data are from the LBD.

FIGURE A.4: SECTORAL EMPLOYMENT SHARES FOR 2-DIGIT NAICS INDUSTRIES, AVERAGED FROM 1980-2015



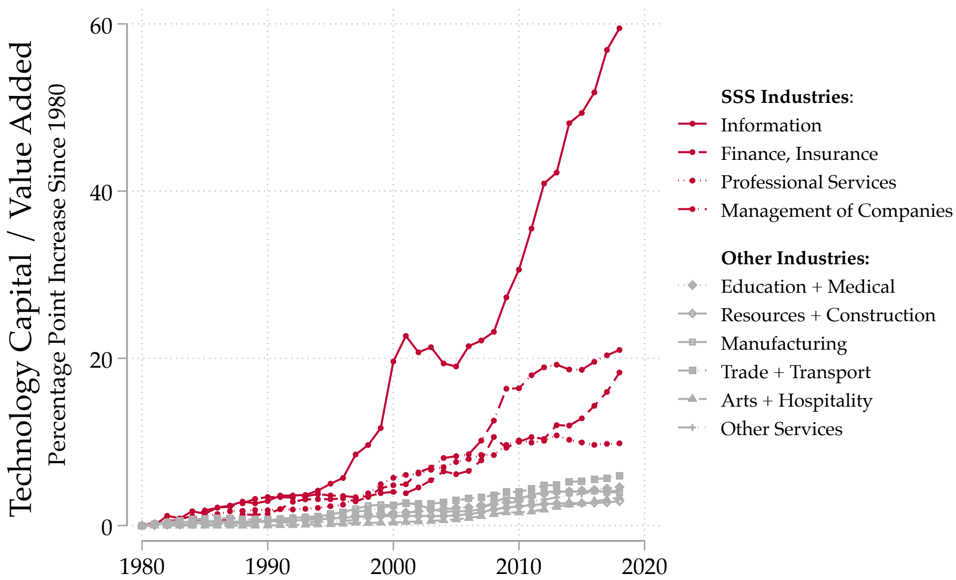
Notes: This figure plots employment shares in 1980 for 2 digit NAICS indsutries, by the ten density decile groups for commuting zones used throughout the paper. The data are from the Decennial Census. Employment shares are normalized by their value in the least dense commuting zone group.

FIGURE A.5: AVERAGE WAGE GROWTH
BY 2-DIGIT NAICS INDUSTRY



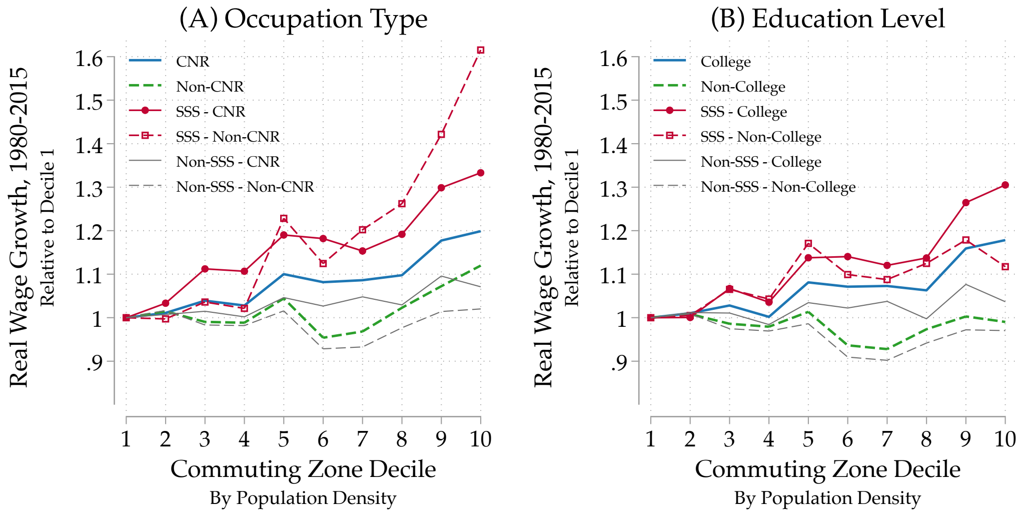
Notes: This figure plots average wages at the industry level relative to 1980 by NAICS 2-digit code. The data are from the QCEW, with consistent industry classifications using the Fort and Klimek (2016) crosswalk to extend the series back to 1980. The data is adjusted by the BLS CPI-U.

FIGURE A.6: CAPITAL DEEPENING
BY 2-DIGIT NAICS INDUSTRY



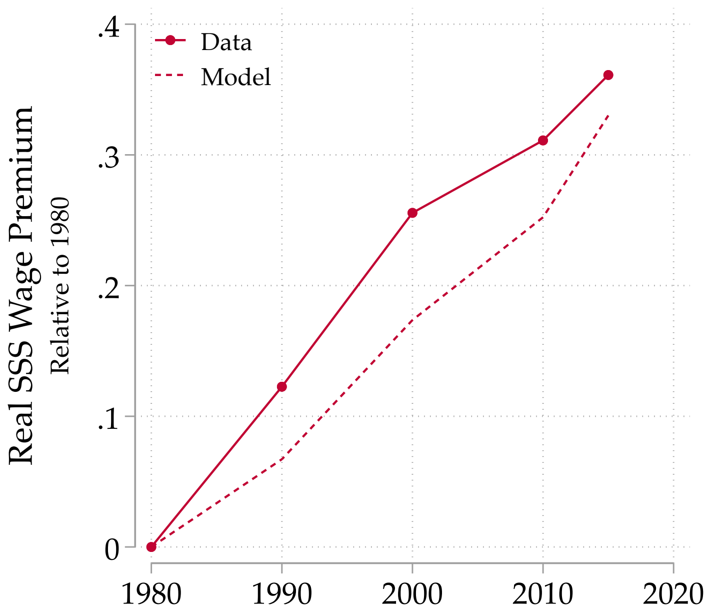
Notes: This figure plots the increase since 1980 in ICT capital (software and hardware) as a fraction of the total real value added by year for major industry groupings. Capital stocks are deflated by the equipment price index for each series. The data are from the BEA.

Figure A.7: Average Wage Growth Across Commuting Zones by Sector, Occupation, and Education Group



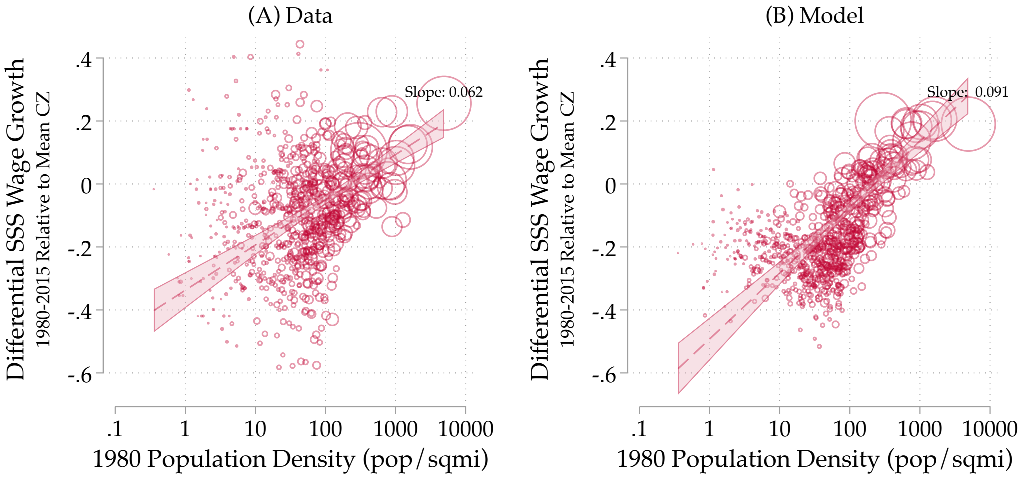
Notes: This figure plots average wage growth by occupation (Panel (A)) and education (Panel (B)) across the 10 density decile groupings used in the paper, relative to the first decile. The data are from the Decennial Census (1980) and the ACS (2015), adjusted by the BLS CPI-U.

FIGURE A.8: SKILLED SCALABLE SERVICES WAGE PREMIUM IN DATA AND MODEL



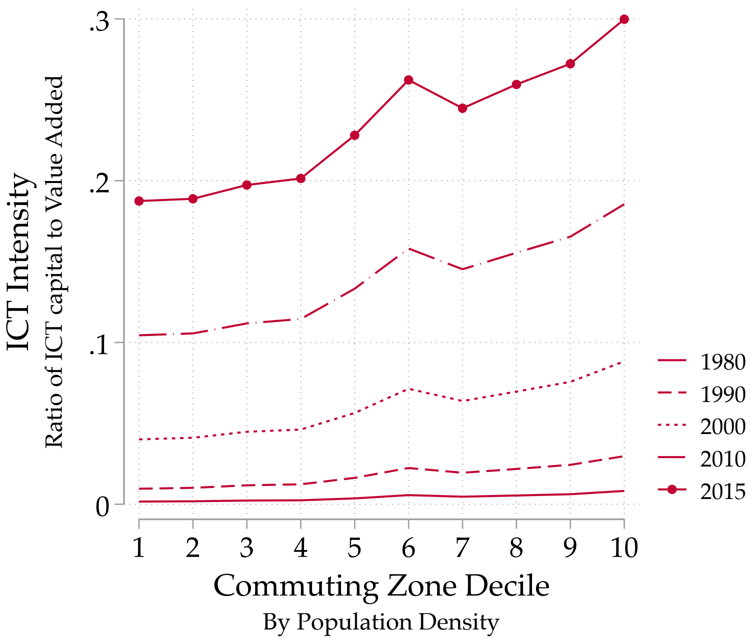
Notes: This figure plots the SSS wage premium above non-SSS in log points relative to 1980, for both model (dashed line), and data (solid line). The wage premium is the log difference in mean sectoral wages between SSS and non-SSS. Data used are the Decennial Census (1980-2000) and American Community Survey (2010-2015), adjusted by the BLS CPI-U.

FIGURE A.9: SKILLED SCALABLE SERVICES WAGE PREMIUM GROWTH IN DATA AND MODEL ACROSS COMMUTING ZONES



Notes: This figure plots the difference in average wage growth between SSS and non-SSS at the commuting zone level between 1980 and 2015. The left panel is the data and the right is the predictions of the model. The average change is demeaned to center around zero. Size of circles is 1980 population. Regressions weighted by the 1980 commuting zone population. Alaskan commuting zones are omitted. The data are from the Decennial Census (1980) and ACS (2015), adjusted by the BLS CPI-U.

FIGURE A.10: SKILLED SCALABLE SERVICES ICT CAPITAL STOCK IN THE MODEL ACROSS COMMUTING ZONES



Notes: This figure shows predicted ICT capital stocks by year and commuting zone density decile group from the model.

TABLE A.1: EMPLOYMENT SHARES AND REAL WAGES
ACROSS COMMUTING ZONE GROUPSBY EDUCATION GROUP AND SECTOR

Sample			Commuting Zone Density Decile									
Year	SSS	College	1	2	3	4	5	6	7	8	9	10
(A) Employment Shares												
1980			0.73	0.74	0.72	0.72	0.68	0.66	0.66	0.63	0.63	0.60
1980		✓	0.18	0.17	0.18	0.18	0.20	0.21	0.21	0.23	0.23	0.22
1980	✓		0.07	0.07	0.07	0.07	0.08	0.09	0.08	0.09	0.09	0.11
1980	✓	✓	0.03	0.02	0.03	0.03	0.04	0.04	0.04	0.06	0.05	0.07
2015			0.65	0.64	0.60	0.58	0.52	0.54	0.51	0.47	0.45	0.44
2015		✓	0.25	0.25	0.27	0.28	0.30	0.29	0.32	0.33	0.35	0.33
2015	✓		0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.07	0.06	0.05
2015	✓	✓	0.05	0.05	0.07	0.08	0.11	0.11	0.11	0.14	0.15	0.18
(B) Real Wages (2015 ’000 USD)												
1980			42	40	42	42	43	47	47	46	49	47
1980		✓	56	56	59	60	62	68	66	68	67	69
1980	✓		42	41	42	42	43	48	45	46	48	50
1980	✓	✓	64	63	63	64	67	72	71	75	73	79
2015			43	41	42	42	44	43	43	44	48	47
2015		✓	66	67	71	70	75	82	81	81	86	85
2015	✓		48	46	51	49	57	60	55	59	64	63
2015	✓	✓	82	81	87	86	98	106	102	110	119	132
(C) Sectoral Real Wages (2015 ’000 USD)												
1980		n/a	45	43	46	46	48	52	52	52	53	53
1980	✓	n/a	48	46	48	48	51	56	54	57	57	61
2015		n/a	50	49	51	51	55	57	58	59	65	63
2015	✓	n/a	64	63	70	69	83	89	85	94	104	117

Notes: Panel (A) lists the share of workers by sector and educational attainment within a commuting zone decile for 1980 and 2015. Panel (B) table lists average wages in thousands of 2015 dollars for full time, prime age workers by sector and educational attainment in 1980 and in 2015. Panel (C) table lists average wages in thousands of 2015 dollars for full time, prime age workers by sector in 1980 and in 2015. Commuting zones deciles are ordered by 1980 population density, with 1 being the least dense and 10 being the most dense. The data are from the Decennial Census (1980) and ACS (2015), adjusted by the BLS CPI-U.

TABLE A.2: REAL WAGES BY SECTOR IN THE 25 LARGEST COMMUTING ZONES (2015 USD ’000)

Commuting Zone			**Wages (’1000)**			
			Non-SSS		**SSS**	
Main Metro Area and State	1980 Pop	Decile	1980	2015	1980	2015
Los Angeles-Long Beach-Anaheim, California	11,510,106	6	53.0	55.7	58.3	89.6
New York–Newark–Jersey City, New York	10,621,244	10	50.3	62.0	60.3	126.4
Chicago-Naperville-Elgin, Illinois	7,171,437	10	55.6	61.3	61.3	100.1
New York–Newark–Jersey City, New Jersey	5,267,294	10	53.9	66.5	64.5	118.6
Philadelphia-Camden-Wilmington, Pennsylvania	5,190,486	9	51.0	61.7	56.5	95.5
Detroit-Livonia-Dearborn, Michigan	5,180,483	9	61.4	60.6	60.0	78.8
Boston-Cambridge-Quincy, Massachusetts	4,457,165	9	49.5	68.9	56.7	113.1
San Francisco–Oakland–Fremont, California	3,585,007	9	55.9	74.2	58.7	129.2
Washington-Arlington-Alexandria, Virginia	3,333,528	8	57.4	70.5	63.2	109.3
Hartford-West Hartford-East Hartford, Connecticut	3,107,564	8	52.6	65.1	60.6	124.1
Houston-Baytown-Sugar Land, Texas	3,000,051	7	55.7	61.9	60.1	92.0
Pittsburgh, Pennsylvania	2,781,748	8	52.7	58.4	54.7	78.5
Cleveland-Elyria-Mentor, Ohio	2,663,368	9	53.5	56.1	56.4	77.4
Seattle–Tacoma–Bellevue, Washington	2,560,096	5	55.8	65.9	55.3	103.3
Miami-Fort Lauderdale-Pompano Beach, Florida	2,398,314	8	46.4	52.6	53.9	80.0
Buffalo-Cheektowaga-Tonawanda, New York	2,368,543	7	51.6	54.5	48.9	69.3
Baltimore-Towson, Maryland	2,173,989	9	50.7	65.0	55.7	91.9
Minneapolis-St. Paul-Bloomington, Minnesota	2,168,282	7	54.8	63.9	56.5	88.0
St. Louis, Missouri	2,144,726	7	51.3	56.4	55.1	81.8
Atlanta-Sandy Springs-Marietta, Georgia	2,051,508	7	48.9	55.5	54.3	91.1
Dallas-Plano-Irving, Texas	1,985,086	7	51.0	58.3	54.2	89.7
San Diego-Carlsbad-San Marcos, California	1,861,846	8	51.1	59.8	53.8	90.5
San Jose-Sunnyvale-Santa Clara, California	1,798,661	6	57.9	78.5	61.5	131.2
Cincinnati-Middletown, Ohio	1,711,354	8	52.3	58.3	53.8	80.5
Denver-Aurora, Colorado	1,640,393	5	53.4	60.8	55.8	91.4

Notes: This table lists average wage in thousands of 2015 dollars for full time, prime age workers by sector for the 25 largest commuting zones in 1980 and in 2015. The data are from the Decennial Census (1980) and ACS (2015), adjusted by the BLS CPI-U.

B. Decomposing Average Wage Growth

In the paper, we show average wage growth patterns in the aggregate and across commuting zones. Fact 2 also documents changes in education composition within the SSS industries. In this section, we provide a formal decomposition of average wage growth in SSS into changes in education group specific wages, and changes in the composition of the sector's workforce.

We index education groups by e and express average wages at time t as follows:

$$w_t = w_{t-1} + \underbrace{\sum_e \lambda^e_{t-1} \Delta w^e_t}_{\text{Changes in Wages}} + \underbrace{\sum_e \Delta \lambda^e_t w^e_{t-1}}_{\text{Changes in Composition}} + \underbrace{\sum_e \Delta \lambda^e_t \Delta w^e_t}_{\text{Covariance}}, \tag{A.1}$$

where we defined $\Delta x_t \equiv x_t - x_{t-1}$ for some variable x_t, and where λ^e denotes the fraction of education group e among the workforce at time t.

Equation (A.1) decomposes the level of the average wage across all education groups at time t into four components: its level in the last period, wage growth within each education group holding the composition of the workforce fixed, changes in the composition of the workforce holding wages within each education group fixed, and the covariance between wage growth and compositional changes. We apply this decomposition to average wages in the SSS sector across time, but also to the average wages in the SSS sector within each commuting zone decile over time. In both cases, we can construct counterfactual wage series that would have pertained had only wages within education groups changed, or had only the composition of the sector but not within group wages changed.

We start by decomposing the growth of SSS wages in the aggregate economy. We carry out this decomposition in the public-use decennial census data which has the information on the education of employees unavailable in the LBD data. Table A.4 presents the results. It shows the fraction of average wage growth accounted for by each component of equation (A.1) in the aggregate, and within the bottom and top decile of commuting zones in terms of density. We compute these shares by subtracting the $t-1$ wage from both sides of equation (A.1) and then dividing both sides by the left hand side wage change. This yields the fraction of the wage change attributable to each of the three right hand side components.

Table A.4 shows that wage growth within education group explains the majority of average wage growth in SSS since 1980. Changes in composition are also important, the education deepening of the sector accounts for about a quarter of average wage growth between 1980 and 2015.[46] The increase in the covariance component over time (see top panel of Table A.4) reflects that initially SSS wages grew fastest for more skilled SSS workers, but it took some time for skilled workers to start moving into SSS disproportionately. In more recent year, wage growth in SSS has still been fastest for more educated

[46]Of course, there are may also be unobserved compositional changes within education groups whereby the smartest college graduates increasingly sort into certain sectors.

TABLE A.3: The Urban Bias in Occupation, Education, and SSS Wage Growth

	Growth in Average Commuting Zone Wage between 1980 and 2015							
	Skilled Scalable Services				All Other Industries			
Occupation Group	Cognitive Non-Routine		All Other		Cognitive Non-Routine		All Other	
Commuting Zones Population Density (1980, Logs)	0.0395***	0.0692***	0.0216***	0.119***	0.00804*	0.0226***	-0.00699	0.00355
	(0.00629)	(0.00762)	(0.00609)	(0.0126)	(0.00314)	(0.00425)	(0.00382)	(0.00805)
Population Weighted		✓		✓		✓		✓
Adjusted R^2	0.062	0.336	0.018	0.506	0.012	0.123	0.007	0.001
N	741	741	741	741	741	741	741	741
Education Group	College or More		Less than College		College or More		Less than College	
Commuting Zones Population Density (1980, Logs)	0.0275***	0.0719***	0.0278***	0.0341***	0.00728*	0.0160***	-0.0109**	-0.00732
	(0.00683)	(0.00889)	(0.00502)	(0.00720)	(0.00319)	(0.00458)	(0.00340)	(0.0395)
Population Weighted		✓		✓		✓		✓
Adjusted R^2	0.022	0.320	0.052	0.129	0.008	0.062	0.023	0.010
N	741	741	741	741	741	741	741	741

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: We use samples of the U.S. Census Data obtained from for 1980 and the American Community Survey Data for 2015 obtained from IPUMS. We use the PUMA identifiers in the data to allocate each observation to a commuting zone as defined by Tolbert and Sizer (1996) using the crosswalks provided by David, Dorn, and Hanson (2013). We then compute average wages of full time, prime aged workers within each commuting zone, sector, and either occupation or education group for both years. We then regress wage growth in a commuting zone, sector, and either occupation (top panel) or education group (bottom panel) on the log population density of the associated commuting zone in 1980. Weighted regression are weighted by total workers in each bin. We follow Jaimovich and Siu (2020) and Rossi-Hansberg et al. (2019), and define CNR occupations to include occupations with SOC-2 classifications 11 to 29 and non-CNR occupations to include the remainder of SOC-2 classifications. Skilled Scalable Services industries are those with NAICS-2 codes 51, 52, 54, and 55.

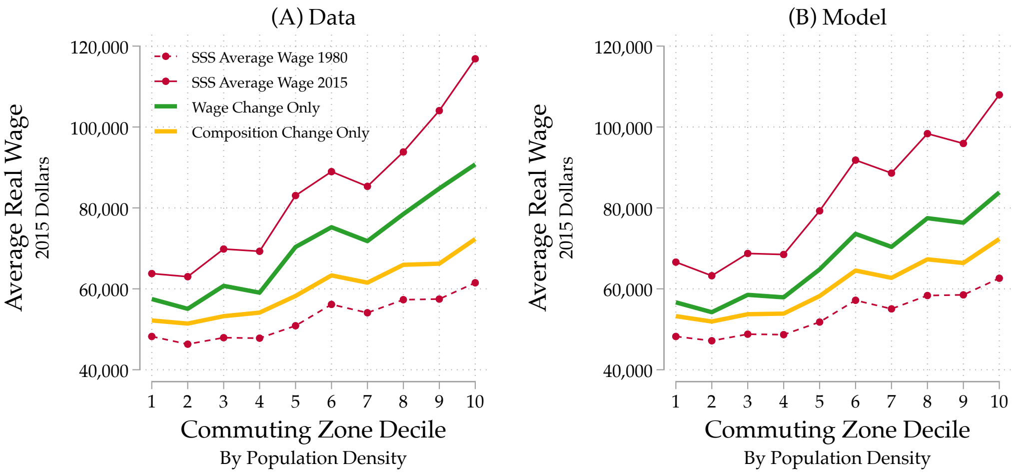
workers *but at the same time* these workers have drastically increased their employment share among the SSS workforce, making the covariance component more, and the wage growth component less important.

Next, we decompose the average wage growth *within* each commuting zone decile into the three components of Equation A.1. The left panel of Figure A.11 plots average wages in SSS across commuting zones ordered by increasing density for 1980 and 2015. It shows two additional lines. The green line shows the average wages across commuting zones in 2015 that would have resulted had there only been differential local changes in wages within education groups, holding the distribution of workers across these education groups fixed. The yellow line shows the wage gradient in 2015 if only compositional changes had occurred, and wages had been fixed at their 1980 level. Figure A.11 makes clear that wage changes within education groups are responsible for the majority of SSS wage growth in all commuting zones. Figure A.12 shows the exact same four wage series as the left panel of Figure A.11, but all relative to the first density decile within each series to highlight the strength of the urban bias of each. Within education group, wage growth exhibits by far the most urban bias of all three components, compositional changes are happening in all commuting zones and are only mildly biased towards denser locations.

Overall within education group wage growth drives SSS wage growth in the aggregate, within each commuting zone, and also its urban bias across commuting zones.

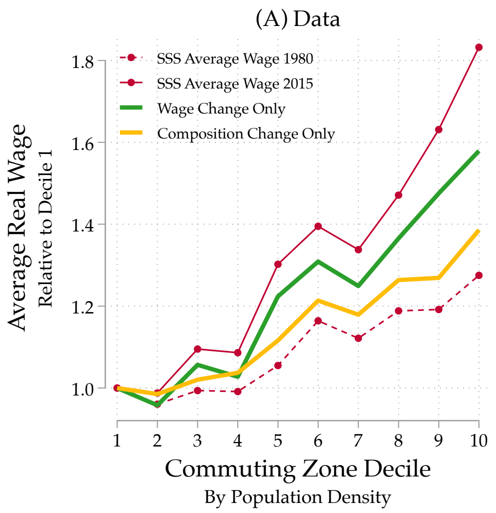
We replicate these decomposition in the model generated data to see whether the model agrees with the data on the underlying margins of the urban-biased growth in SSS. The right panel of Figure A.11 repeats the decomposition within each commuting zone group in the model generated data. The figure shows that in model and data, the key engine behind urban-biased average wage growth is within education group wage growth.

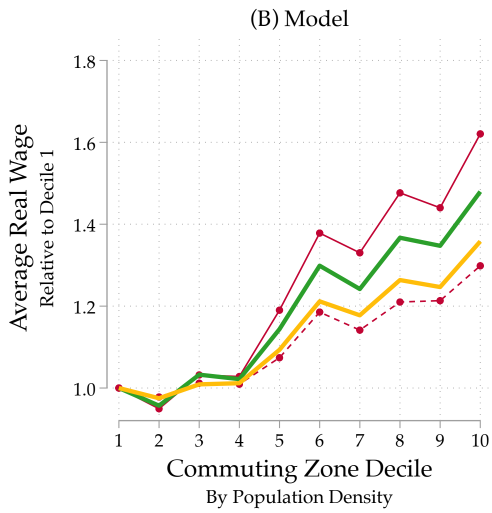
FIGURE A.11: DECOMPOSING SKILLED SCALABLE SERVICES AVERAGE WAGE GROWTH ACROSS COMMUTING ZONES IN DATA AND MODEL



Notes: This figure plots average wages for SSS within the ten density deciles used throughout the paper into three components as described in equation (A.1). The red lines are data for 1980 and 2015. The green line shows what wages would have been if education shares within each decile were held constant at their 1980 values. The yellow line shows average wage within deciles if only education shares varied, and wages within education groups were held at their 1980 values. Panel (A) reflects the raw data. Panel (B) reflects model generated data after 1980. The data used is the Decennial Census (1980-2010) and the ACS (2015). The data is adjusted by the BLS CPI-U.

FIGURE A.12: DECOMPOSING SKILLED SCALABLE SERVICES AVERAGE WAGE GROWTH ACROSS COMMUTING ZONES





Notes: This figure repeats Figure A.11, but normalises all estimates by their values in the first of the ten density decile groups. Sub-figure (a) reflects the raw data. Sub-figure (b) reflects model generated data after 1980. The data used is the Decennial Census (1980-2010) and the ACS (2015). The data is adjusted by the BLS CPI-U.

Table A.4: Decomposing Skilled Scalable Services Average Wage Growth

	Fraction of SSS Average Wage Growth Accounted for by		
Between 1980 and …	Wage Growth	Compositional Change	covariance
Aggregate Economy			
1990	.73	.21	.05
2000	.69	.17	.15
2010	.60	.21	.19
2015	.55	.22	.22
Top Decile of Commuting Zones			
1990	.76	.17	.07
2000	.70	.14	.16
2010	.59	.17	.24
2015	.54	.19	.28
Bottom Decile of Commuting Zones			
1990	.43	.61	-.03
2000	.69	.21	.1
2010	.63	.24	.13
2015	.61	.26	.13

Notes: This table reports the results of decomposing SSS averages wages according to equation (A.1) across different time periods. Data used is the Decennial Census (1980-2010) and American Community Survey (2015).

C. Estimation Details

C.1 Details on Production Function and Labor Supply Elasticities

Production Function Elasticities Parameters: σ, ϵ, γ. Profit maximization of firm f in location r and sector s yields the following equilibrium condition, equalizing relative marginal products and relative wages:

$$\log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\log\left(\frac{h_f}{l_f}\right) + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\log(y_f) + \frac{1}{\sigma}\log\left(\frac{\alpha^H_{r,s}}{\alpha^L_{r,s}}\right).$$

We take differences across two equilibria and re-index firms by their efficiency:

$$\Delta\log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\Delta\log\left(\frac{h^*(z)}{l^*(z)}\right) + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\Delta\log(y(z)) + \frac{1}{\sigma}\Delta\log\left(\frac{\alpha^H_{r,s}}{\alpha^L_{r,s}}\right),$$

where $h^*(\cdot)$, $l^*(\cdot)$, and $y^*(\cdot)$ are policy functions mapping firm efficiency to optimal quantities.

Next we integrate across firms within each location r and sector s to obtain:

(A.2)
$$\Delta\log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\mathbb{E}_z\left[\Delta\log\left(\frac{h(z)}{l(z)}\right)\right] + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\mathbb{E}_z\left[\Delta\log(y(z))\right] + \frac{1}{\sigma}\Delta\log\left(\frac{\alpha^H_{r,s}}{\alpha^L_{r,s}}\right).$$

Since we lack firm level data, when we estimate equation A.2, we proxy the expected change in firm level skill ratios $\mathbb{E}_z\left(\Delta\log(h(z)/l(z))\right)$ at the commuting zone level with the change in the overall commuting zone level skill ratio $\Delta\log(H_{r,s})/(L_{r,s})$. This introduces two Jensen-inequality issues. First, $\mathbb{E}_z\left(\Delta\log(\cdot)\right) \neq \Delta\log\mathbb{E}_z\left((\cdot)\right)$ and second, $\mathbb{E}_z(h(z)/l(z)) \neq \mathbb{E}_z(h(z))/\mathbb{E}_z(l(z)) = H_{r,s}/L_{r,s}$, where $H_{r,s}$ and $L_{r,s}$ are the total stock of high-education and low-education workers in location r and sector s, respectively.

The equation we estimate in our panel of commuting zones is

$$\Delta\log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right) = -\frac{1}{\sigma}\Delta\log\left(\frac{H_{r,s}}{L_{r,s}}\right) + \frac{\epsilon^H - \epsilon^L}{\gamma\sigma}\Delta\log\left(\frac{Y_{r,s}}{N_{r,s}}\right) + \frac{1}{\sigma}\Delta\log\left(\frac{\alpha^H_{r,s}}{\alpha^L_{r,s}}\right), \tag{A.3}$$

where $H_{r,s}$ is the number of workers with at least a college degree and $L_{r,s}$ is the number of workers with less than a college degree in commuting zones r and sector s. As discussed in the main text, we cannot calibrate parameters to an OLS estimation of (A.2), due both to the simultaneity in the labor supply module, and bias caused by firm choices reacting to $\frac{\alpha^H_{r,s}}{\alpha^L_{r,s}}$. As such, we calibrate parameters to an IV regression that is valid in the world of the model.

We instrument for $\Delta \log(H_{r,s}/L_{r,s})$ with

(A.4) $$B^1_{r,s,t} \equiv \log\left(\frac{X^{LOA}_{r,s,t}}{X^{LOA}_{r,s,t-1}}\right) X_{r,s,t-1},$$

where $X_{r,s} = H_{r,s}/L_{r,s}$ is the skill ratio in region r and sector s, and

$$X^{LOA}_{r,s,t} \equiv \frac{\sum_{r' \in \{1,\ldots,R\} \setminus r} H_{r',s,t}}{\sum_{r' \in \{1,\ldots,R\} \setminus r} L_{r',s,t}}$$

is the leave-one-out within-sector skill ratio. Likewise, we instrument with the leave-one-out payroll growth rate for the percentage change in GDP:

(A.5) $$B^2_{r,s,t} \equiv \log\left(\frac{\sum_{r' \in \{1,\ldots,R\} \setminus r} y_{r',s,t}}{\sum_{r' \in \{1,\ldots,R\} \setminus r} y_{r',s,t-1}}\right).$$

Payroll is a fundamental component of value added measures, and is also better measured than the GDP growth rate.[47]

We estimate the equations over the the 15-year time difference from 2000 to 2015, for which region-industry GDP is available from the BEA. We run the regression separately for each 2-digit NAICS sector and only for commuting zones that have at least 50,0000 people. To control for level differences between industries, we include sector fixed effects.

This gives us an estimate for the elasticity of substitution σ, as well as the model composite $(\epsilon^H - \epsilon^L)/\gamma\sigma$. The curvature parameter γ and the scale elasticity difference $\epsilon^H - \epsilon^L$ are not separately identified from data on production. Indeed, combinations of these two objects can be chosen to deliver identical model outcomes on the transition we study. As such, we normalise $\epsilon^H = 0$, and choose γ to match the 1980 labor share. Together with the estimated model composite, this gives us ϵ^L.

Table A.5 shows the results of our estimation over a single difference from 2000 to 2015, treating each two digit NAICS industry separately.

Column (1) shows estimates from our OLS estimation. Columns (2) and (3) instrument for the employment ratio and sectoral GDP changes respectively. Column 4 shows the estimate of the elasticity of substitution, σ, to be 3.6 and that of the composite parameter, $(\epsilon^H - \epsilon^L)/\gamma\sigma$, to be 0.55.

Labor Supply Elasticities: ϱ^e. We instrument the change in the wage ratio in location r within education group e with the initial wage ratio times the leave-one-out growth rate in that education group and location:

(A.6) $$B^3_{r,t} \equiv \log\left(\frac{\hat{w}^{e,LOA}_{r,t}}{\hat{w}^{e,LOA}_{r,t-1}}\right) \hat{w}^e_{r,t-1},$$

[47] The documentation of the local industry GDP numbers by BEA does not contain much detail. The principal component of their measures of a sector's regional GDP is its payroll that is sourced from administrative data records.

where $\hat{w}^e_{r,t} \equiv w^e_{r,\text{SSS},t} / w^e_{r,\text{Non-SSS},t}$ and $\hat{w}^{e,LOA}_{r,t} \equiv \frac{\sum_{r' \in \{1,\dots,R\} \setminus r} w^e_{r',\text{SSS},t}}{\sum_{r' \in \{1,\dots,R\} \setminus r} w^e_{r',\text{Non-SSS},t}}$.

Table A.6 reports our estimates for sectoral labor supply elasticities. Column 1 and 3 pool results across all education groups e. Columns 2 and 4 report separate results for college-educated and non-college-educated groups.

C.2 Additional Data Moments for Calibration

Figure A.13 reports values for ICT capital relative to industry value-added for SSS and Non-SSS, respectively. This is used to calibrate the parameters β and C. Figure A.14 reports average establishment size by sector and commuting zone using public data from the County Business Patterns. Table A.7 shows the values for the moments targeted in the estimation.

C.3 Inferred Location Fundamentals

Figure A.15 reports the inferred fundamental productivities of locations, $\alpha^e_{r,s}$ which rationalize observed labor demand holding other model parameters fixed. Figure A.16 plots the inferred location amenities A^e_r for each location against the log population in each region. These amenities rationalize observed labor supply given spatial and sectoral labor supply elasticities.

TABLE A.5: ESTIMATION OF PRODUCTION FUNCTION ELASTICITIES

	(1) OLS	(2) IV-Employment Ratios	(3) IV-GDP	(4) IV-Both
Δ Employment Ratio	0.0198	-0.278	0.0166	-0.312
	(0.0144)	(0.0768)	(0.0150)	(0.0885)
Δ GDP	0.000901	0.00953	0.313	0.548
	(0.0194)	(0.0229)	(0.101)	(0.150)
Observations	2901	2901	2901	2901
Sector Fixed Effects	✓	✓	✓	✓

Notes: Robust standard errors in parentheses. The outcome variable is the change in the regional, within-sector, between education group, wage ratio from 2000-2015 ($\Delta \ln w^H_{r,s}/w^L_{r,s}$). See text for instrumental variable details, using initial shares and leave-one-out GDP growth.

TABLE A.6: ESTIMATION OF SECTORAL LABOR ELASTICITIES

	(1) Pooled OLS	(2) OLS	(3) Pooled IV	(4) IV
Δ Wage Ratio	0.162		1.493	
	(0.103)		(0.353)	
Δ Wage Ratio		0.181		1.446
$\times$ High School		(0.121)		(0.384)
Δ Wage Ratio		0.0955		1.687
$\times$ College		(0.185)		(0.885)
Observations	759	759	759	759
Year $\times$ Skill	✓	✓	✓	✓

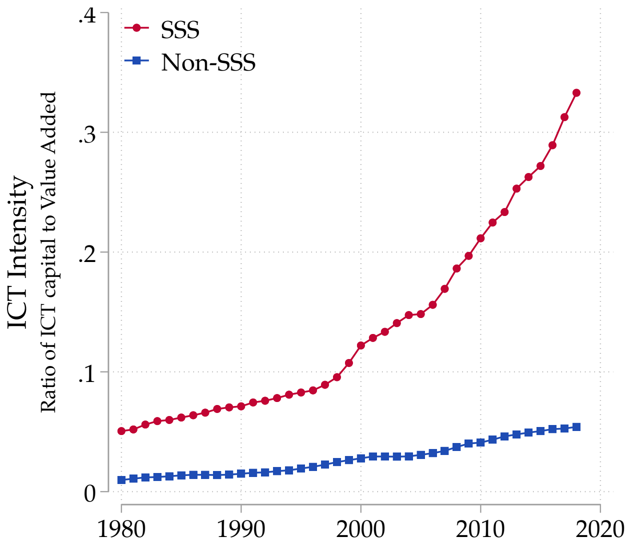
Notes: Robust standard errors in parentheses. The outcome variable is the change in the within-region, within-education group, between sector, employment probability ratio over ten year periods from 1980 to 2010 $\Delta \ln \left[\mathrm{P}_t^e\,(\text{SSS} \mid r)/\mathrm{P}_t^e\,(\text{Non-SSS} \mid r)\right]$. Columns (2) and (4) report interaction terms for two educational groups, those with a college degree or more, or those with a high school degree or less. See text for instrumental variable details, using predicted wage growth.

TABLE A.7: TARGETED MOMENTS IN MODEL AND DATA

Parameter	Value	Moment	Data	MODEL
β	0.62	2015 ICT Share Value Added in SSS	27.2%	27.2%
C	20.9	Share of SSS Adopters in 1980 in SSS	-	10%
ζ_S, ζ_N	0.25,0.13	Elasticity Avg. Estab Size to Population	0.25, 0.23	0.25, 0.23
τ_S, τ_N	1.1,1.9	Average Estab. Size in 1980.	19.8, 20.0	19.8, 20.0
ρ	3.3	SSS Payroll Share in 2015	35%	38%

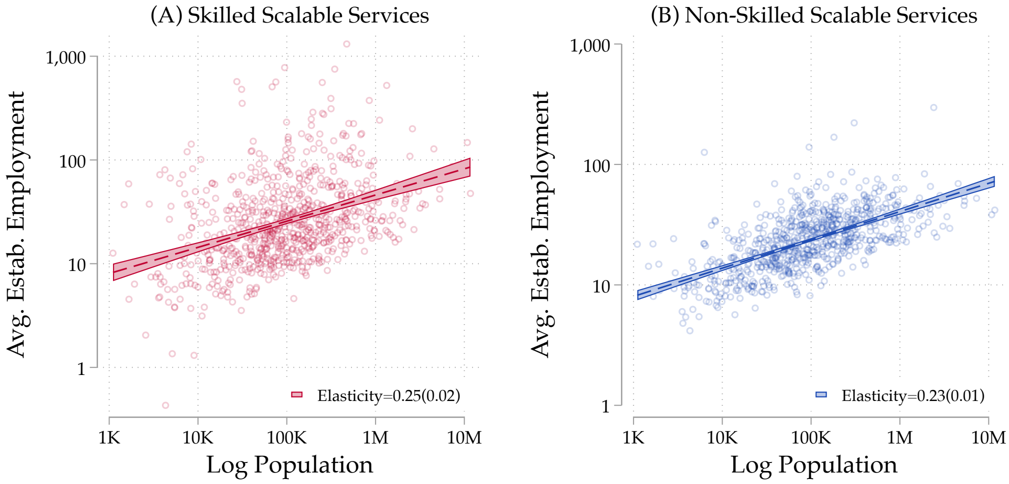
Notes: This table compares the targeted moments for certain model parameters for their values in the data and the values in the model.

FIGURE A.13: ICT CAPITAL SHARE IN VALUE ADDED BY SECTOR



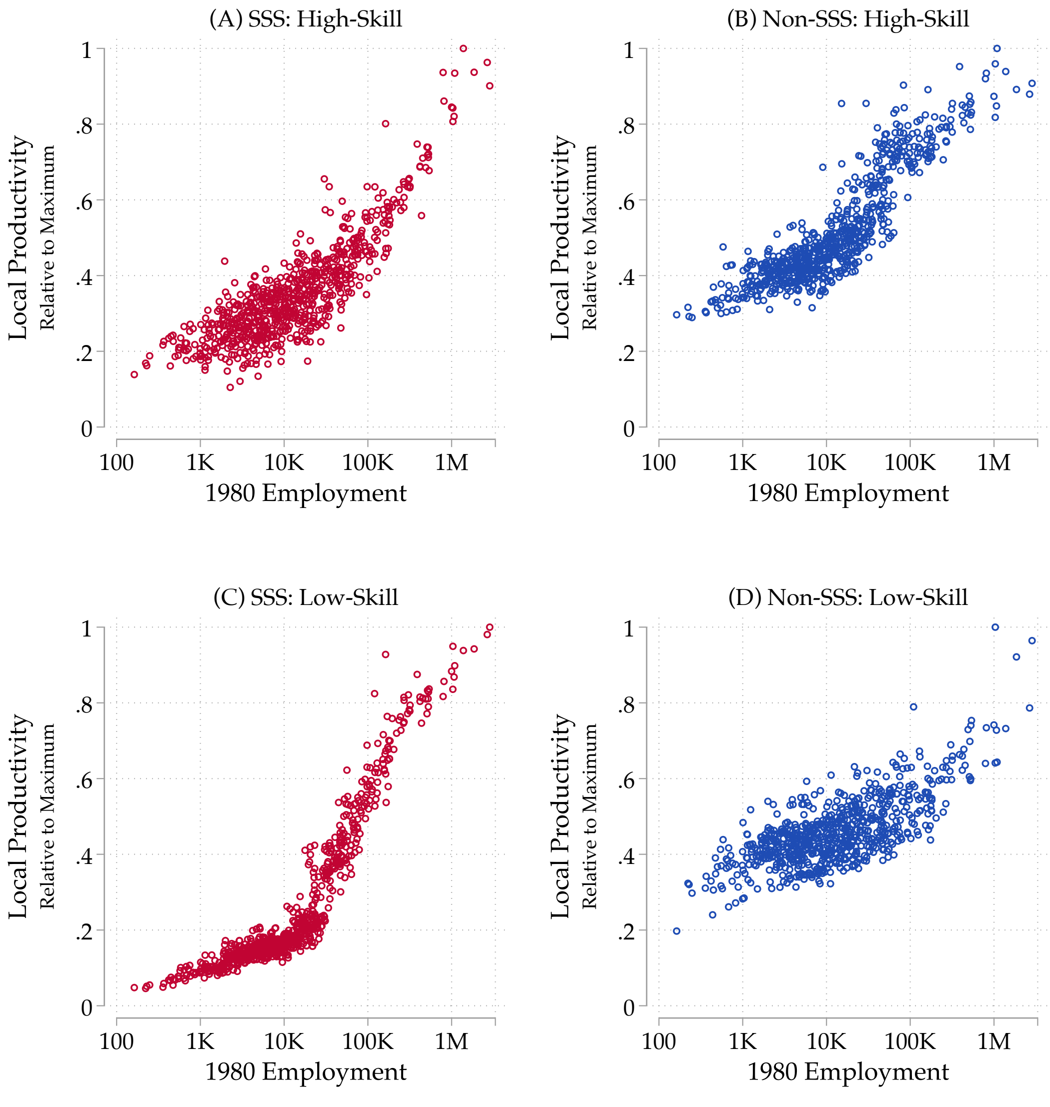
Notes: This figure reports values for ICT capital as a fraction of sectoral value added, for SSS and Non-SSS, respectively. This is used to calibrate the parameters β and C.

FIGURE A.14: AVERAGE ESTABLISHMENT SIZE ACROSS COMMUTING ZONES BY SECTOR



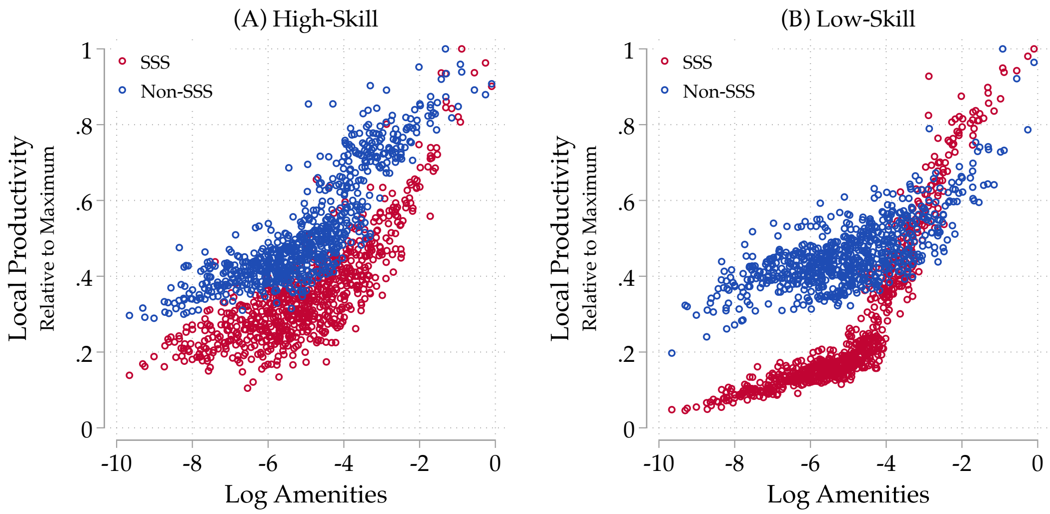
Notes: This figure plots average establishment size by commuting zone population in 1980, for both SSS (red) and Non-SSS (blue). Average establishment size is computed by dividing total employment in the sector and commuting zone by the count of establishments in the sector and commuting zone. The data used are the County Business Patterns. Errors in the underlying source data produce some areas with average establishment size below 1.

FIGURE A.15: LOCATION PRODUCTIVITY ACROSS COMMUTING ZONES
BY SECTOR AND EDUCATION GROUP



Notes: These figures shows the inferred fundamental productivity $\{\alpha^H_{r,s}, \alpha^L_{r,s}\}$ at the calibrated model parameters. Data is for all commuting zones by sector, with SSS in red (left) and Non-SSS in blue (right). Within each group, productivity is normalized as a fraction of the maximum productivity in that group. In the data, high-skill is mapped to college-educated workers and low-skill is mapped to non-college-educated workers.

FIGURE A.16: LOCATION AMENITIES ACROSS COMMUTING ZONES AGAINST LOCAL PRODUCTIVITIES



Notes: This figure plots the estimated structural residuals for commuting zone amenities against local productivity fundamentals by education group and sector. In the data, high-skill is mapped to college-educated workers and low-skill is mapped to non-college-educated workers. Estimates for fundamental productivity are plotted relative to the log of the maximum productivity for that sector, location and group. Amenity residuals only differ by commuting zone and education group, so we relate the same amenities to both SSS and non-SSS productivity for each education group.

D. Additional Data Description

This section summarizes our data sources and sample selection.

D.1 Longitudinal Business Database

The Longitudinal Business Database (LBD) is an administrative restricted-use data set made available by the U.S. Census Bureau and based on the Census' Business Register which is derived from Internal Revenue Service tax data. The database covers the majority of private non-farm employment between 1975 and today.[48] The files contain longitudinally linked data for all U.S. establishments with one or more paid employee(s). For each establishment, information is available on parent firm, industry, zip code, total annual payroll, and total employment count. We use the industry concordances provided by Fort and Klimek (2016) to reclassify all data on a consistent NAICS 2012 industry basis from 1980 to 2015. We compute the establishment-level average wage by dividing the total payroll by total employment in each year. We follow Autor and Dorn (2013) in defining local labor markets based on the concept of commuting zones developed by Tolbert and Sizer (1996).[49] The union of all commuting zones covers the entire territory of the United States. These commuting zones serve as the spatial unit of analysis in all of our paper.

D.2 U.S. Decennial Census Data and American Community Survey

The United States Decennial Census (Census) and the American Community Survey (ACS) are constitutionally mandated nationally representative surveys conducted. While the Census is carried our once every decade, the ACS has been carried out once every year since 2000. We use the Census Integrated Public Use Micro Samples for the years 1980, 1990, and 2000, and the ACS for 2010 and 2015 (Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander (2015)). There are two important issues with these data. First, contrary to the administrative records in the LBD, in surveys respondents self-report. Second, income data are top-coded, whereby the highest incomes are censored in the public-use data. Both issues are important in reconciling the slight differences in findings across the data sets we use. We discuss these differences in more detail in the Online Appendix.

We follow Autor and Dorn (2013) in our sample selection procedure. Our sample consists of individuals who were between age 16 and 64 and who worked in the year pre-

[48] The LBD does not cover Agriculture, Forestry, and Fishing (SIC Division A), railroads (SIC 40), U.S. Postal Service (SIC 43), Certificated Passenger Air Carriers (part of SIC 4512), Elementary and Secondary Schools (SIC 821), Colleges and Universities (SIC 822), Labor Organizations (SIC 863), Political Organizations (SIC 865), Religious Organizations (SIC 866), and Public Administration (SIC Division J) (see Jarmin and Miranda (2002) for details). "Education" in our classification of services in Figure 2 refers to "Trade schools, tutoring, and business schools" which are included in the data.

[49] Tolbert and Sizer (1996) used county-level commuting data from the 1990 Census to create 741 clusters of counties that exhibit large commuting flows within and weak ones across their boundaries.

ceding the survey. Our main measure of annual wages is each respondent's total pre-tax wage and salary income, i.e., money received as an employee, for the previous year. Sources of income in the data include wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. Payments-in-kind or reimbursements for business expenses are not included. We constructed a crosswalk to map the industry identifiers in the data to a consistent NAICS 2012 basis throughout the decades. All calculations are weighted by the Census sampling weight. We assign workers into one of four educational categories: high school or less, some college, college, more than college. With the help of the crosswalk provided by Autor and Dorn (2013), we map the geographic identifiers in the data to the commuting zones (CZ) developed by Tolbert and Sizer (1996).

D.3 Quarterly Census of Employment and Wages

We also document some of our facts using the LBD data in another source of administrative data, the Quarterly Census of Employment and Wages (QCEW). The QCEW contains comprehensive employment and payroll data for U.S. establishments by industry and location and is published by the Bureau of Labor Statistics. Different from the LBD, the QCEW is derived from records of the state and federal unemployment insurance programs. A notable limitation of the QCEW data is that the Bureau of Labor Satistics only started to provide them on a NAICS 2012 basis from 1990 onward. Prior to 1990, we use the Fort and Klimek (2016) crosswalk to link SIC codes with NAICS codes. Another limitation of the data is that it contains many missing observations on the county level which are suppressed due to privacy concerns. As a result, we only use the data for the aggregate U.S. economy.

D.4 Data on Information and Communication Technology Adoption

To understand technology adoption and capital, we use the Bureau of Economic Analysis' (BEA) Fixed Asset and GDP-by-Industry tables, along with the U.S. Census Bureau's Annual Capital Expenditures Survey (ACES) and Information & Communication Technology Survey (ICTS).

We use two elements of the BEA fixed asset tables. Our source for ICT capital prices are the BEA's GDP deflators for private investment. For data on ICT capital stocks by industry, we draw on the BEA's detailed files for "Fixed-Cost Net Capital Stock of Private Nonresidential Fixed Assets." In particular, we combine Hardware (asset codes EP1-EP31) and Software (asset codes ENS1-ENS3) into our measure of ICT capital. We combine this with total industry value added from the BEA's GDP-by-Industry data series for our calibration exercise. We map industries to a consistent NAICS 2012 2-digit basis using Fort and Klimek (2016)

To measure technology adoption across commuting zones we draw on two firm-level surveys conducted by the the Census Bureau in 2007 and 2012, the ACES and ICTS. [50] In 2007 and 2012, we allocate all software investment to a firm's establishments, proportional to the establishment's share of employment in the firm's total employment. We then aggregate all establishments in a commuting-zone-industry bin to an aggregate software and employment total using Census sampling weights. For Figure 6 in Section 2, we pool the information on adoption across the two survey years, 2007 and 2012. We also computed a version of this figure for single-establishment firms only which looks qualitatively the same.

D.5 County Level GDP

To calibrate the production function in our model, we use the BEA's local area GDP estimates, which are provided at the county-industry level from 2001 onwards. We use the "CAGDP2" dataset, that covers country level data by 2-digit NAICS code. We map the geographic identifiers in the data to the CZ developed by Tolbert and Sizer (1996)).

D.6 County Business Patterns

For the estimation of the firm supply elasticity, we use the establishment counts by industry for each county from the County Business Patterns. In the County Business Patterns, employment numbers are suppressed for some industry and county combinations. We use the imputation of these numbers provided by Eckert et al. (2019) to compute average establishment size by industry for each of the CZ in the U.S.

[50] We use question 5, that asks "Report capital expenditures for computer software developed or obtained for internal use during the year."