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

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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
JEL Codes: J31, O33, R11, R12

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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 wage gap 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

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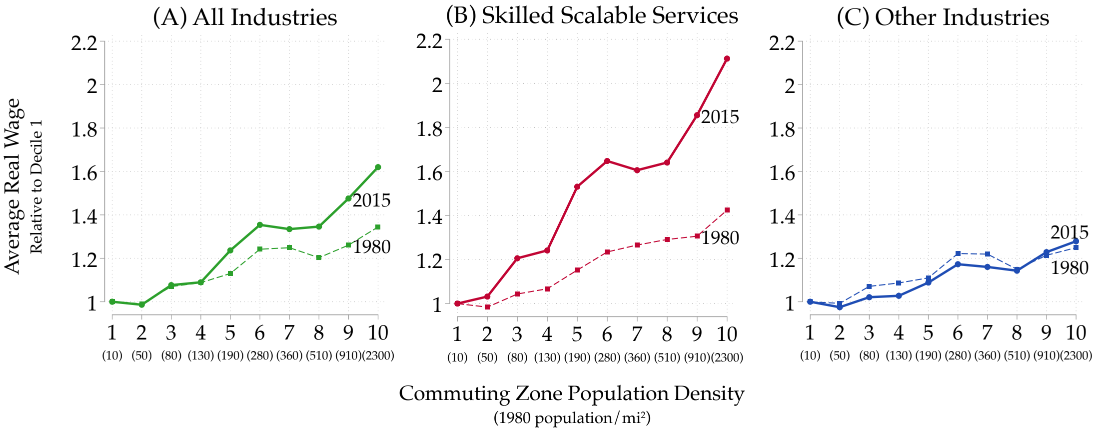
[1] Approximately half of U.S. workers lived in cities less dense than Orlando, Florida, in 1980.

[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

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[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-

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[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

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[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)). Jiao and Tian (????) are an exception studying the effect of internet quality on spatial sorting for different skill groups.

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-

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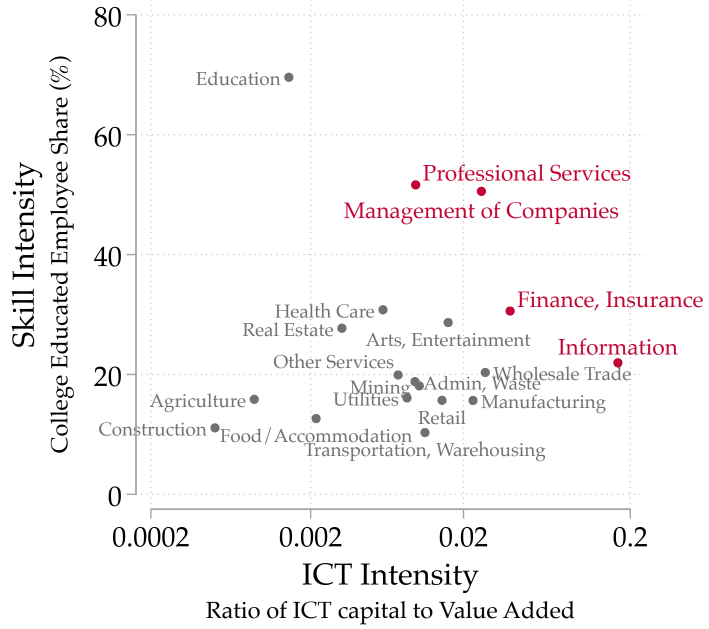
[10] There is a nascent literature on the role of services in explaining the recent changes in spatial organization of economic activity. Hsieh and Rossi-Hansberg (2019) document that recently "chain" service firms such as hospitals or supermarkets, aided by ICT technology, have expanded their stores 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.

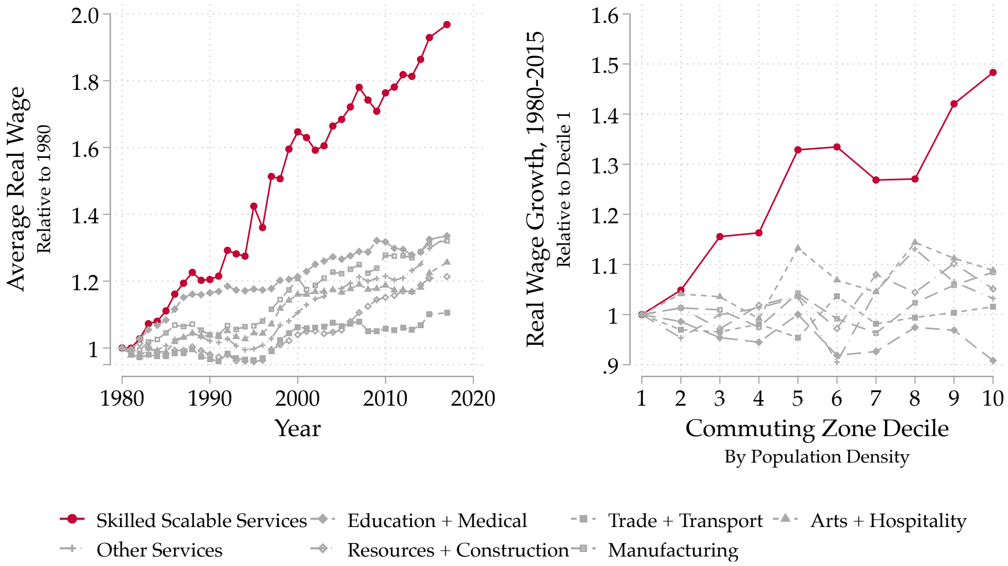
Skilled Scalable Services accounted for about 17% of aggregate employment in the U.S. economy in 1980, a number that has little in subsequent decades. . Employment shares in Skilled Scalable Services increased rapidly in local population density – more than any other 2-digit industry – both in 1980 and 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

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[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

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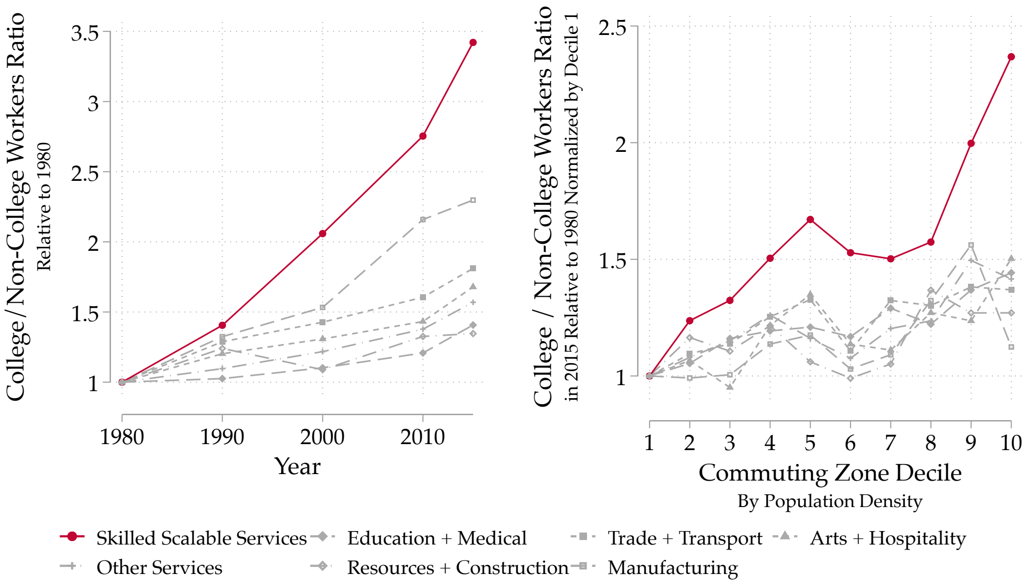
United States. In supplementary material we provide the complete mapping of all commuting zones to density deciles. An alternative way to construct this graph is to order commuting zones by increasing population *size*. Figures using population size instead of population density appear very similar to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

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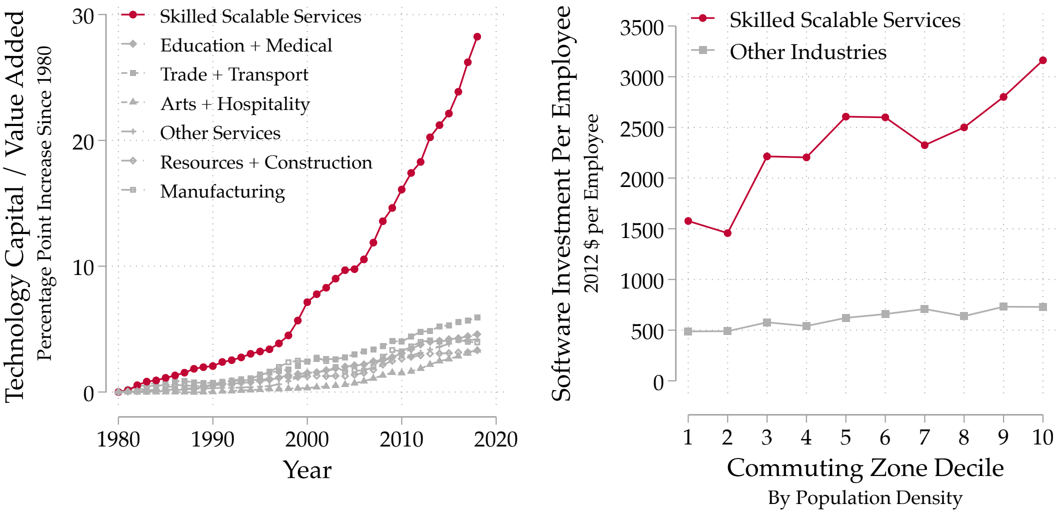
[18] Figure A.6 in the Appendix reports the same statistic for each individual 2-digit NAICS industry. It shows that the disproportionate adoption of ICT capital occurs in each of the four SSS industries individually. Each one of them adds significant more percentage points than any other sector in the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

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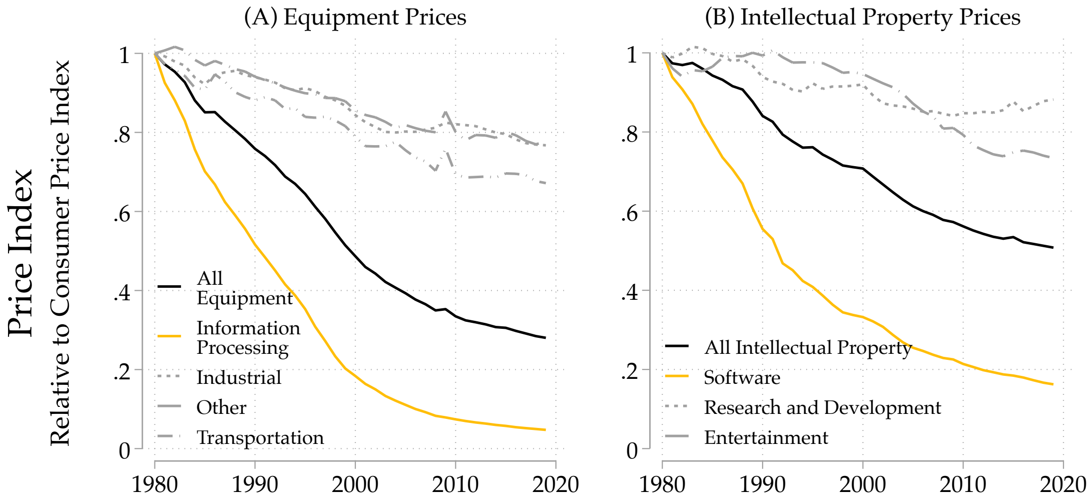
[19] To construct this graph we rely on a survey conducted by U.S. Census on firms between 2007 and 2012. To construct the figure we average ICT investments over multiple waves of the survey, and allocate software to a firm's establishments in proportion to employment.

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.

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[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

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[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,

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

where $\tilde{z}_f$ denotes *firm productivity* and the $\alpha^H_{r,s}$ and $\alpha^L_{r,s}$ 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

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[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 $w_{r,s}^e$. 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_r^i, and from working in sector s in location r, $\xi_{r,s}^i$. 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

$$\bar{v}^e = \mathbb{E}_\eta[\max_r\{\eta_r^i \times \mathbb{E}_\xi[\max_s\{w_{r,s}^e \times \xi_{r,s}^i\}]\}]. \tag{3}$$

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:

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

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:

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

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 $y_{r,s}^{\not I}(z, h, \{w_{r,s}^e\})$ denotes the firm's output if it does not adopt ICT, incorporating the optimal choice of low-skill labor from equation (4), denoted $l_{r,s}^*(y, h, \{w_{r,s}^e\})$. Similarly, the function $y_{r,s}^I(z, h, \{w_{r,s}^e\}, p^K)$ denotes the output of a firm that adopts ICT capital, where optimal capital investment is taken from equation (5), denoted $k_{r,s}^*(y, h, \{w_{r,s}^e\}, p^K)$.

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:

$$\begin{aligned} \pi_{r,s}^*(z) = \max\Big\{ & \max_h \; p_s y_{r,s}^{\not I}(z, h, \{w_{r,s}^e\}) - w_r^H h - w_r^L l_{r,s}^*(h, y^{\not I}, \{w_{r,s}^e\}), \\ & \max_h p_s y_{r,s}^I(z, h, \{w_{r,s}^e\}, p^K) - w_r^H h \\ & - w_r^L l_{r,s}^*(h, y^I, \{w_{r,s}^e\}) - p^K k_{r,s}^*(h, y^I, \{w_{r,s}^e\}, p^K) - C \Big\}. \end{aligned} \tag{6}$$

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 $z_{r,s}^*(\{w_{r,s}^e\}, p^K)$ adopt ICT capital. As a result, *average firm productivity* in location r and sector s, denoted $\bar{Z}_{r,s}$, satisfies:

$$\bar{Z}_{r,s} = \int_0^{\infty} z dG(z) + \int_{z_{r,s}^*(\{w_{r,s}^e\}, p^K)}^{\infty} z k^*(y_{r,s}^*(z), h_{r,s}^*(z), \{w_{r,s}^e\}, p^K)^{\beta} dG(z). \tag{7}$$

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.

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[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 $Y^*_s(p^s, \{Y_{s'\neq s}\})$.

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[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:

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

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

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

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:

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

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-

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

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

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.

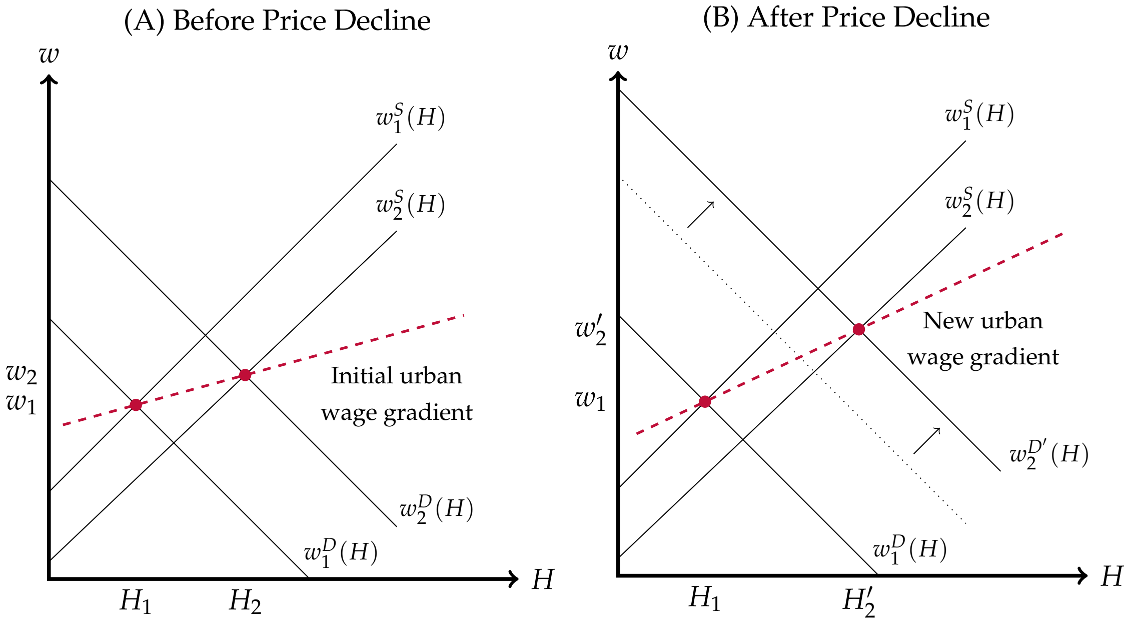
Now consider equation (13). Its left hand side can be shown to be a strictly increasing one-to-one function of the adjusted wage on $\mathbb{R}_+$, while its right hand side is a strictly decreasing one-to-one function of the adjusted wage on the same domain. As a result, equation (13) uniquely determines 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


(A) Before Price Decline

(B) After Price Decline

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

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

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.

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[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

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

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 $\nu_{r,s}^{Y}$ 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 $\alpha_{r,s}^{H}/\alpha_{r,s}^{L}$ and amenities $\{A_r^e, D_{r,s}^e\}$ 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:

$$\Delta \log\left(\frac{P^{e}\left(\text{SSS} \mid r\right)}{P^{e}\left(\text{Non-SSS} \mid r\right)}\right) = \varrho \Delta \log\left(\frac{w_{r,\text{SSS}}^{e}}{w_{r,\text{Non-SSS}}^{e}}\right) + \psi_r^e, \tag{16}$$

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

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[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]

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[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 Elastictity	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

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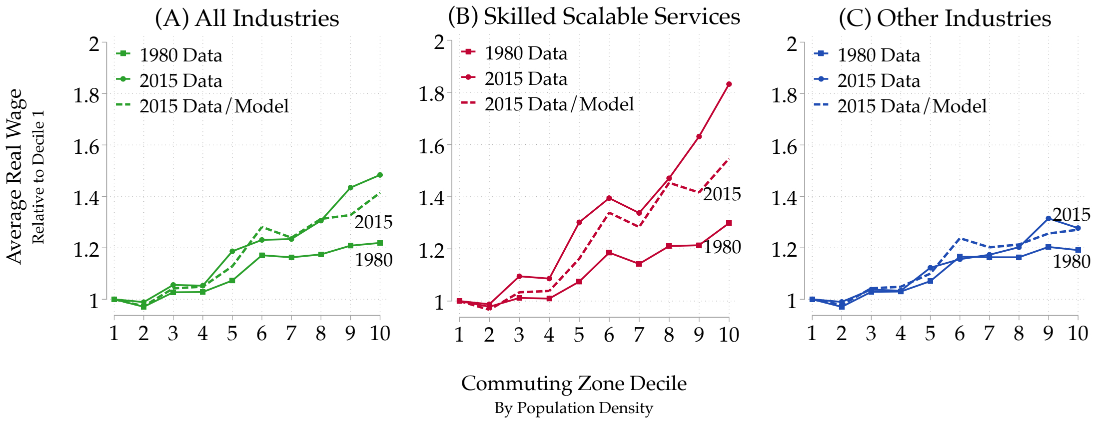
[40] To measure average establishment size across space, we obtain total employment and the number of establishments for all U.S. commuting zones and industries in 1980 from the County Business Patterns data using the imputations provided by Eckert, Fort, Schott, and Yang (2019).

[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

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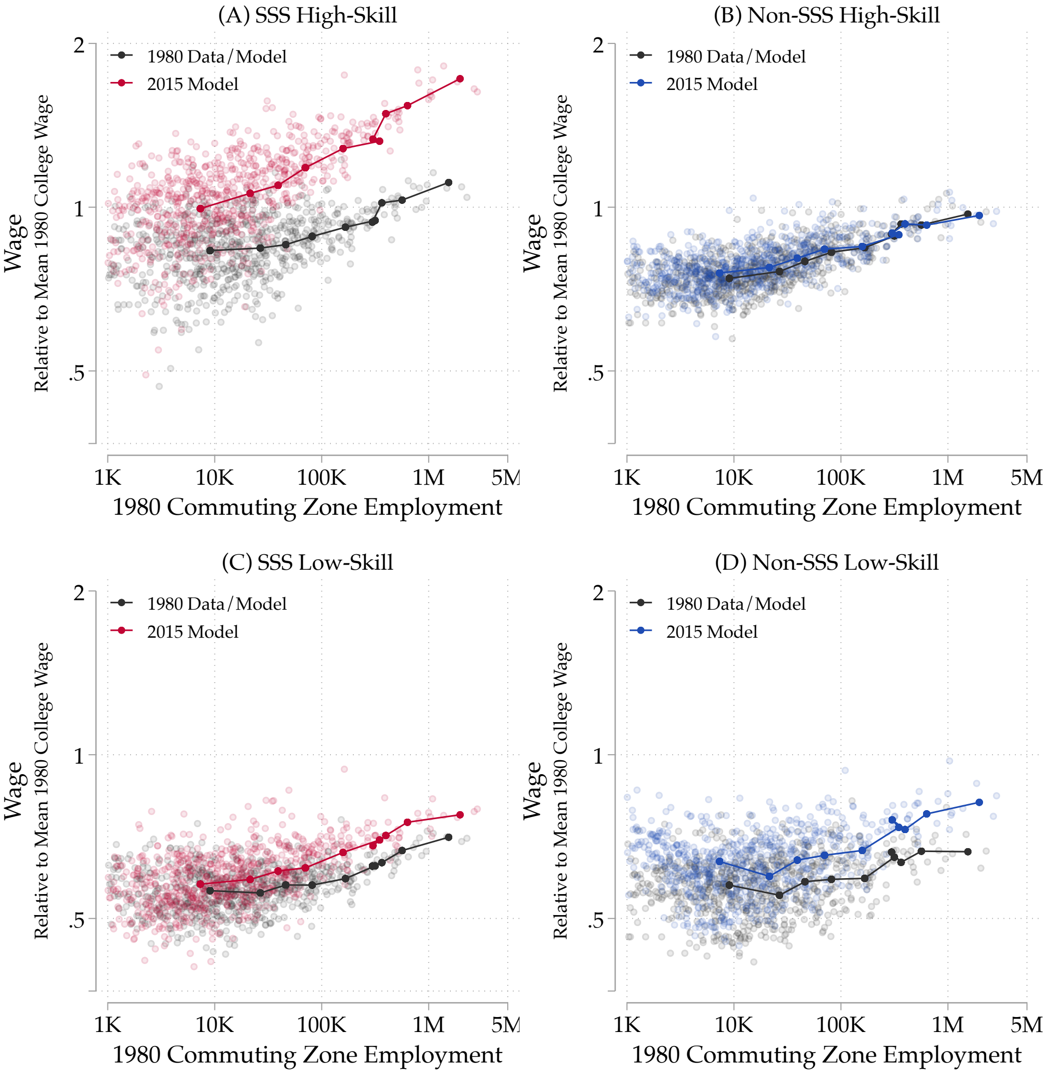
[42] Figure 8 replicates Figure 1 from the introduction in the Census data we use to calibrate the model. We cannot use the LBD data for the calibration of the model since we require data on educational attainment of the labor force within each commuting zone, which is not available in the LBD. In the 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

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[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.

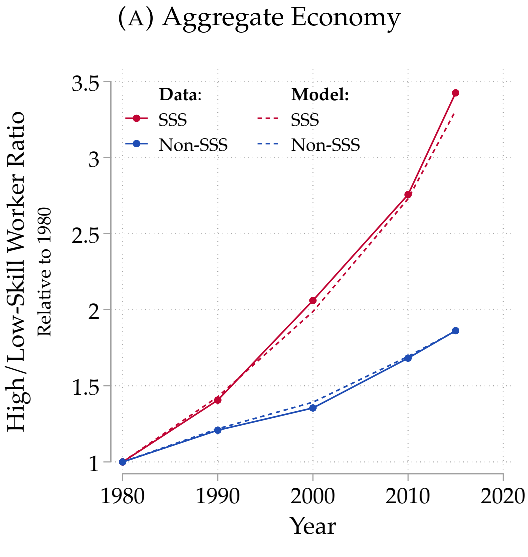
Overall, the decline in the ICT price generates labor demand that is biased towards skilled workers and larger commuting zones with higher population density. While part of this labor demand shock is reflected in wages, the upward sloping labor supply implies that some of it is reflected in compositional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


(A) Aggregate Economy

(B) Across Regions

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

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[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.

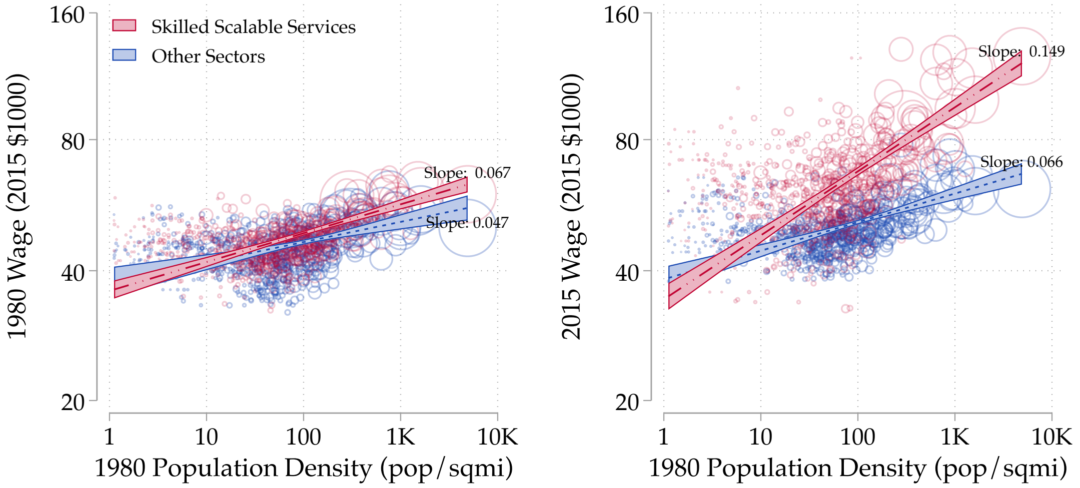
A.2 Tables

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.

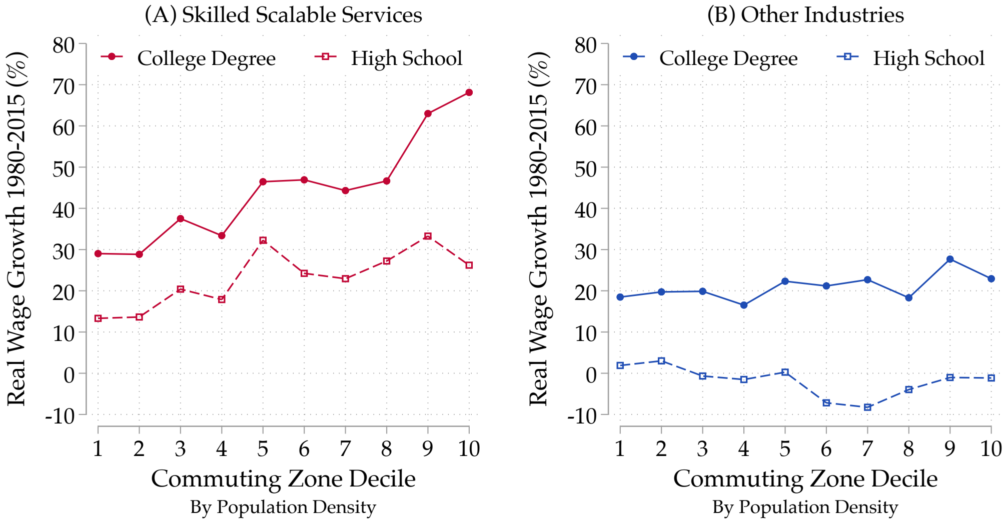
Table A.3 provides more detail on the urban bias of wage growth in occupation groups, education groups, and industries. We run separate regression for the growth of commuting-zone-level average wages of CNR workers in SSS and Non-SSS, and college-educated workers in SSS and Non-SSS on population density. 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



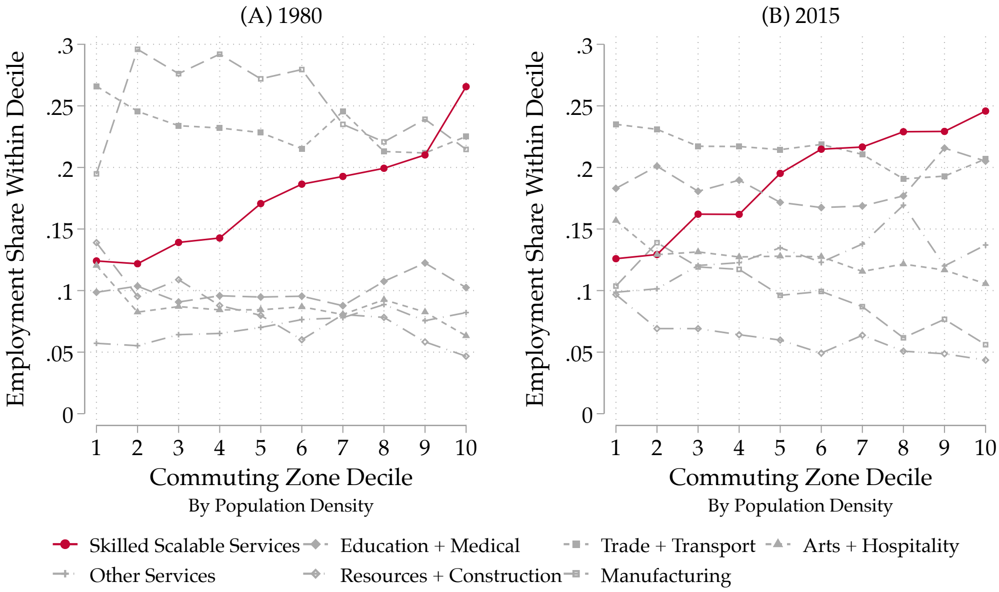
Notes: The left panel of this figure plots average wages at the commuting zone and sector level against commuting zone density in 1980. Size of circles is 1980 population. The right panel does the same for 2015. All wages are in 2015 dollars. Alaskan commuting zones and eight commuting zones under 1 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



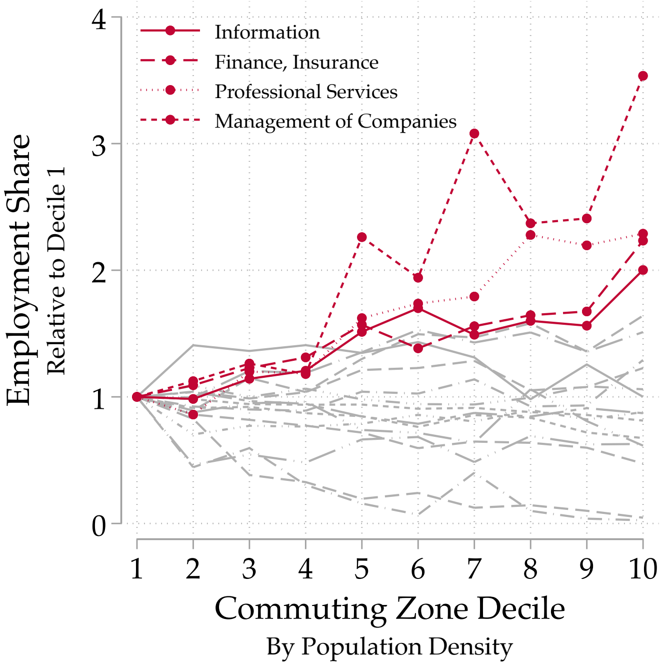
Notes: This figure plots average wage growth between 1980 and 2015 by the 10 commuting zone density deciles used throughout the paper. Panel (A) shows the SSS industries and Panel (B) shows all other industries. The data are from the Decennial Census (1980) and the ACS (2015), adjusted by the BLS CPI-U.

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



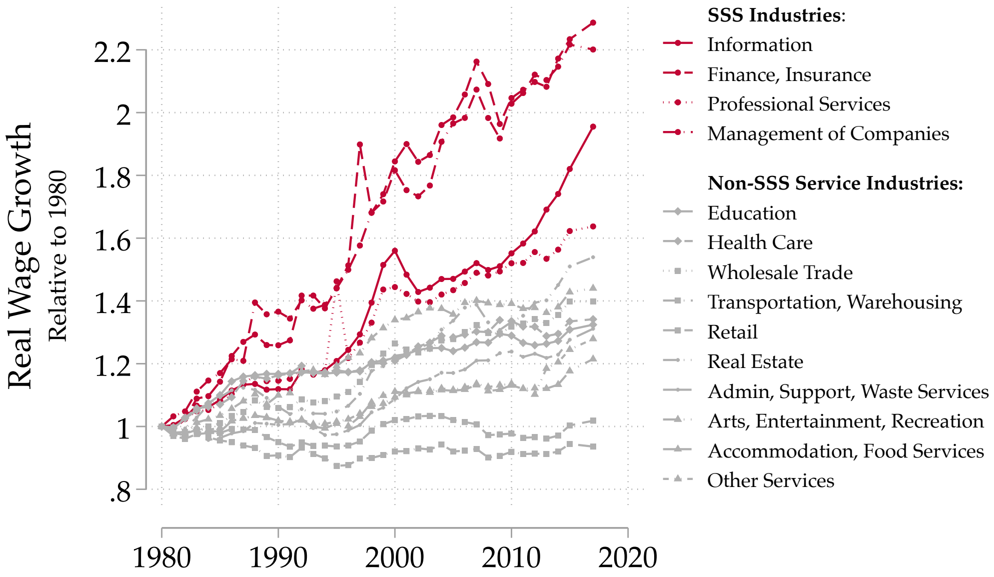
Notes: This figure plots employment shares in 1980 (Panel (a)) and 2015 (Panel (b)) for major industry groupings, by the ten density decile groups for commuting zones used throughout the paper. The data are from the LBD.

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



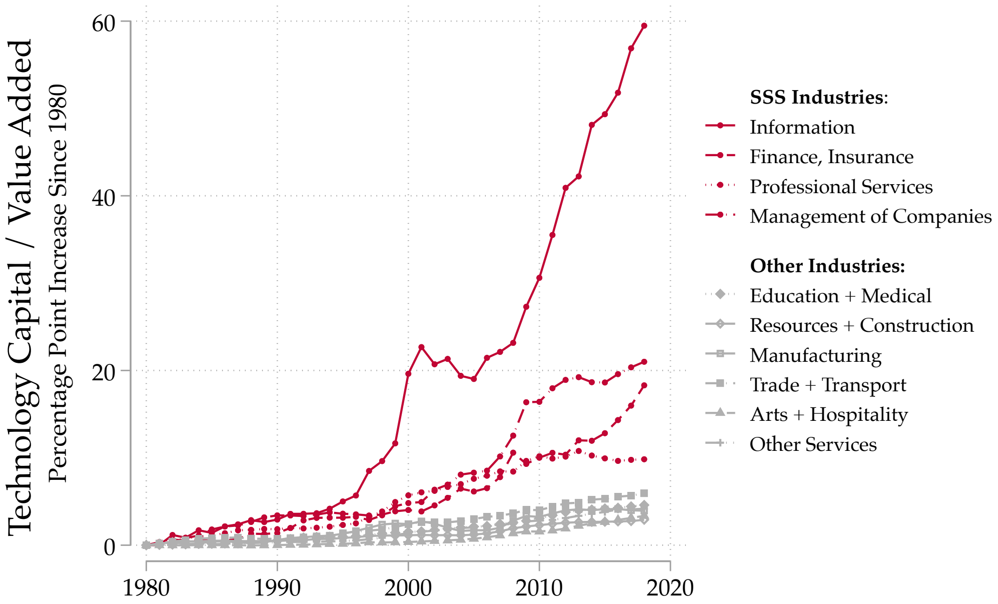
Notes: This figure plots employment shares in 1980 for 2 digit NAICS indsutries, by the ten density decile groups for commuting zones used throughout the paper. The data are from the Decennial Census. Employment shares are normalized by their value in the least dense commuting zone group.

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



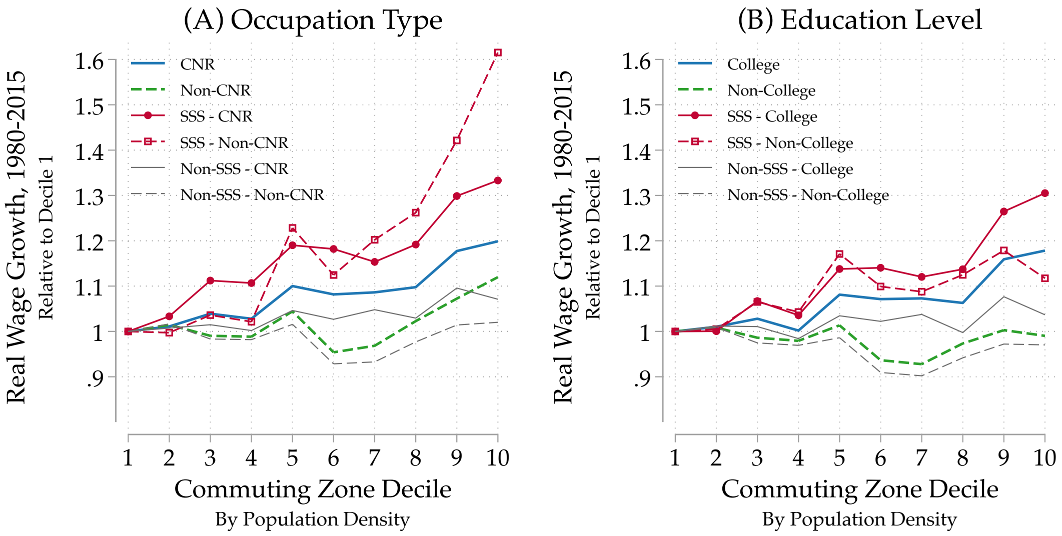
Notes: This figure plots average wages at the industry level relative to 1980 by NAICS 2-digit code. The data are from the QCEW, with consistent industry classifications using the Fort and Klimek (2016) crosswalk to extend the series back to 1980. The data is adjusted by the BLS CPI-U.

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.

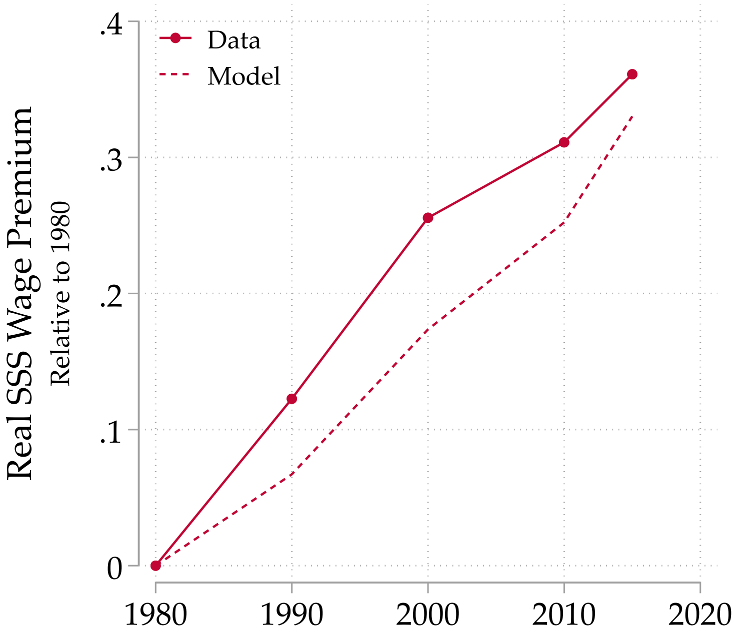
FIGURE A.7: AVERAGE WAGE GROWTH ACROSS COMMUTING ZONES BY SECTOR, OCCUPATION, AND EDUCATION GROUP


(A) Occupation Type

(B) Education Level

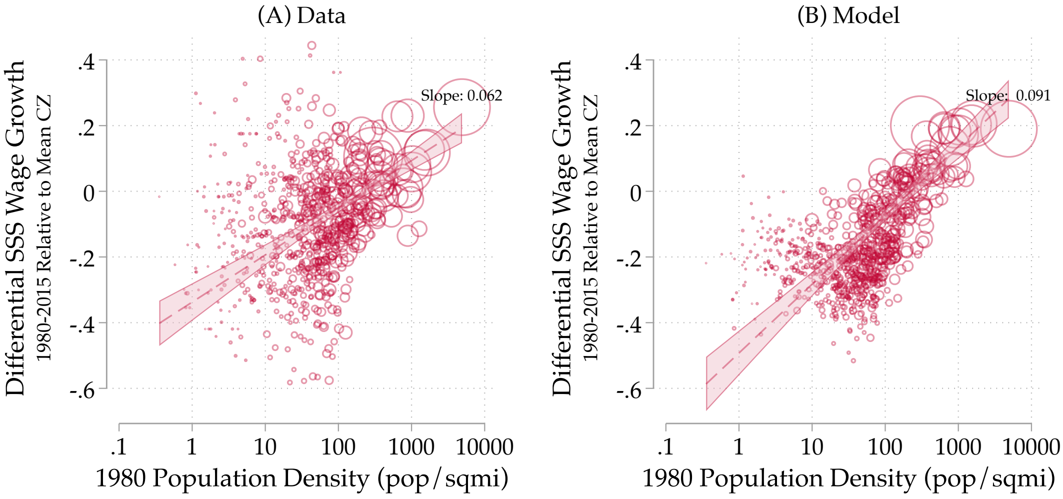
Notes: This figure plots average wage growth by occupation (Panel (A)) and education (Panel (B)) across the 10 density decile groupings used in the paper, relative to the first decile. The data are from the Decennial Census (1980) and the ACS (2015), adjusted by the BLS CPI-U.

Figure A.8: Skilled Scalable Services Wage Premium in Data and Model



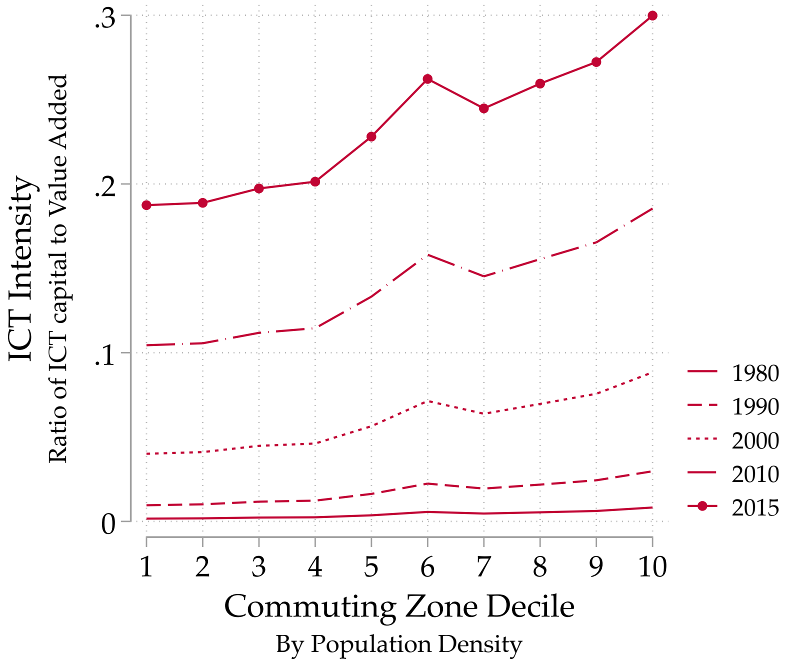
Notes: This figure plots the SSS wage premium above non-SSS in log points relative to 1980, for both model (dashed line), and data (solid line). The wage premium is the log difference in mean sectoral wages between SSS and non-SSS. Data used are the Decennial Census (1980-2000) and American Community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

			Wages (’1000)			
Commuting Zone			**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:

$$w_t = w_{t-1} + \underbrace{\sum_e \lambda_{t-1}^e \Delta w_t^e}_{\text{Changes in Wages}} + \underbrace{\sum_e \Delta\lambda_t^e w_{t-1}^e}_{\text{Changes in Composition}} + \underbrace{\sum_e \Delta\lambda_t^e \Delta w_t^e}_{\text{Covariance}}, \tag{A.1}$$

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

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[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.

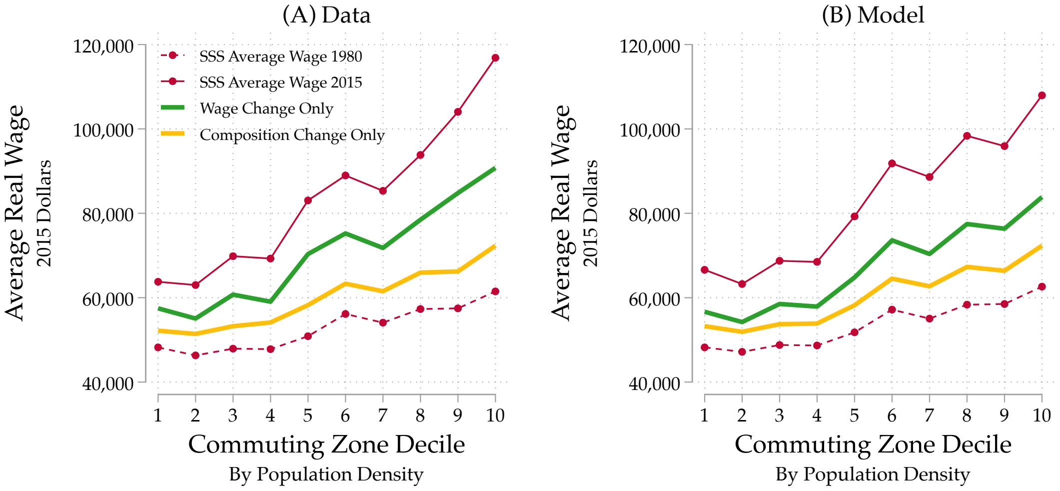
workers *but at the same time* these workers have drastically increased their employment share among the SSS workforce, making the covariance component more, and the wage growth component less important.

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.

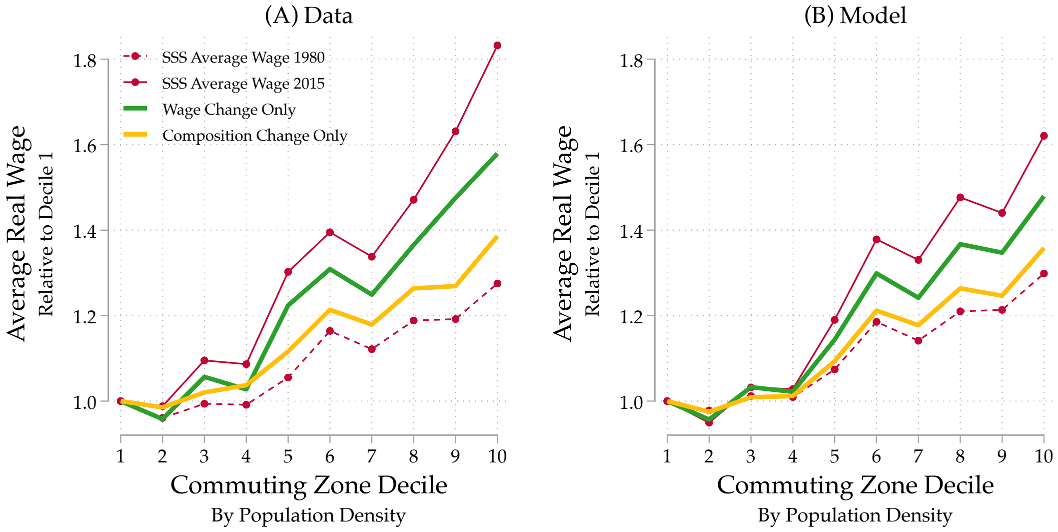
We replicate these decomposition in the model generated data to see whether the model agrees with the data on the underlying margins of the urban-biased growth in SSS. The right panel of Figure A.11 repeats the decomposition within each commuting zone group in the model generated data. The figure shows 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

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

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

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

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:

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

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:

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

---

[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 $\hat{w}^{e,LOA}_{r,t} \equiv \frac{\sum_{r' \in \{1,\ldots,R\} \setminus r} w^e_{r',\text{SSS},t}}{\sum_{r' \in \{1,\ldots,R\} \setminus r} w^e_{r',\text{Non-SSS},t}}$.
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
× High School		(0.121)		(0.384)
Δ Wage Ratio		0.0955		1.687
× College		(0.185)		(0.885)
Observations	759	759	759	759
Year × Skill	✓	✓	✓	✓

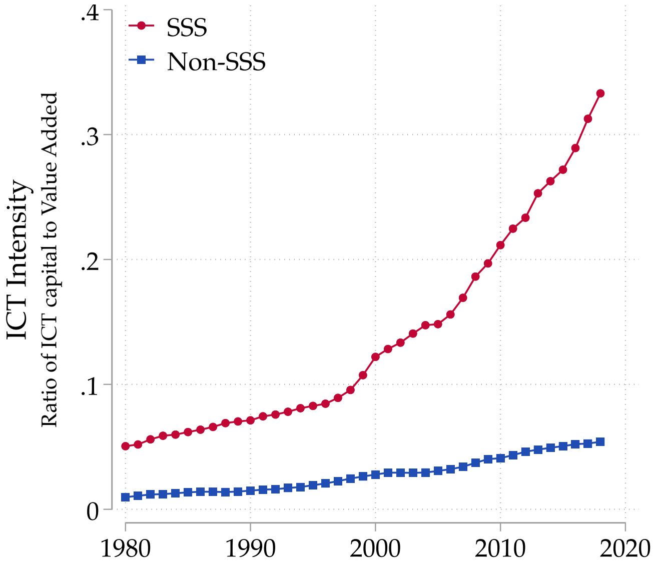
Notes: Robust standard errors in parentheses. The outcome variable is the change in the within-region, within-education group, between sector, employment probability ratio over ten year periods from 1980 to 2010 $\Delta \ln [\mathrm{P}_t^e\,(\text{SSS} \mid r)/\mathrm{P}_t^e\,(\text{Non-SSS} \mid r)]$. 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%

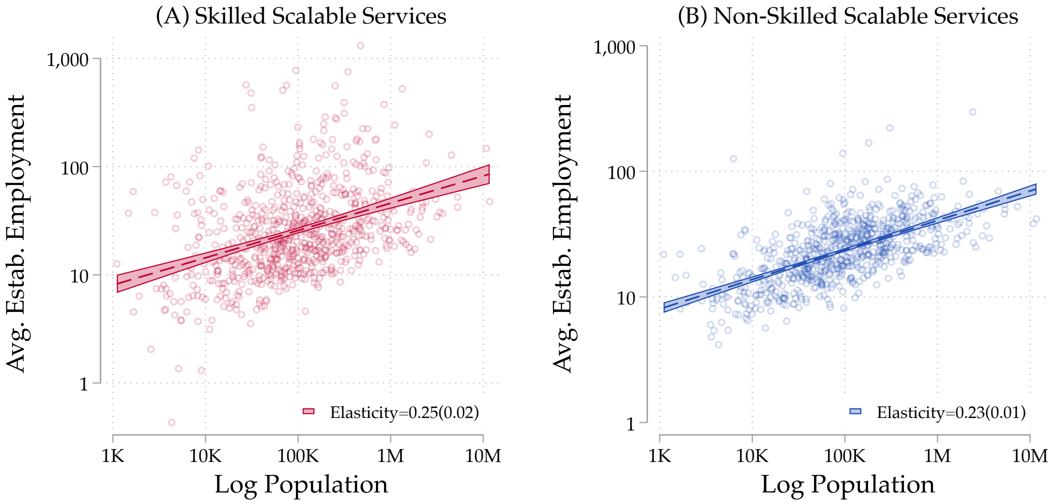
Notes: This table compares the targeted moments for certain model parameters for their values in the data and the values in the model.

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



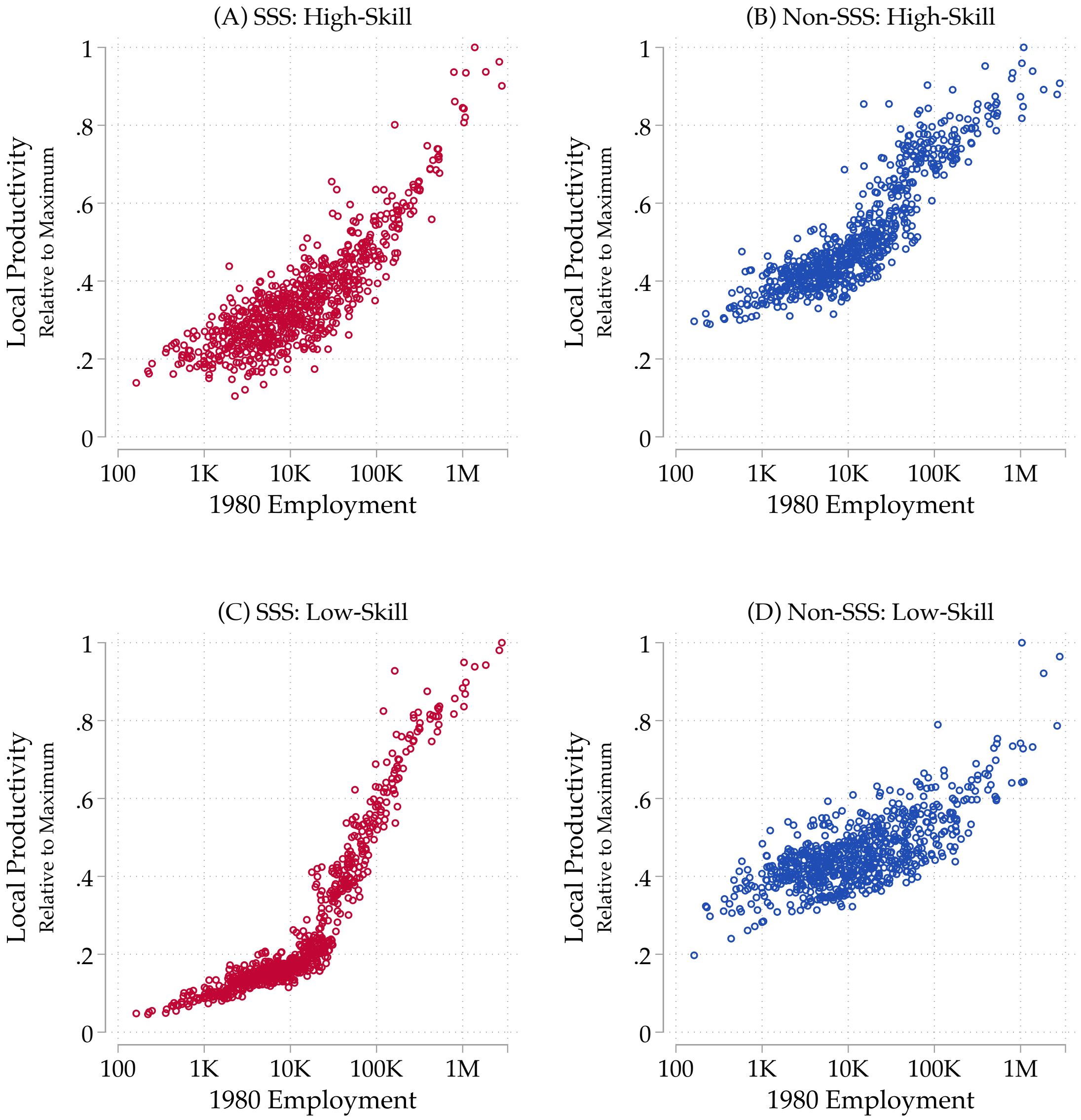
Notes: This figure reports values for ICT capital as a fraction of sectoral value added, for SSS and Non-SSS, respectively. This is used to calibrate the parameters β and C.

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



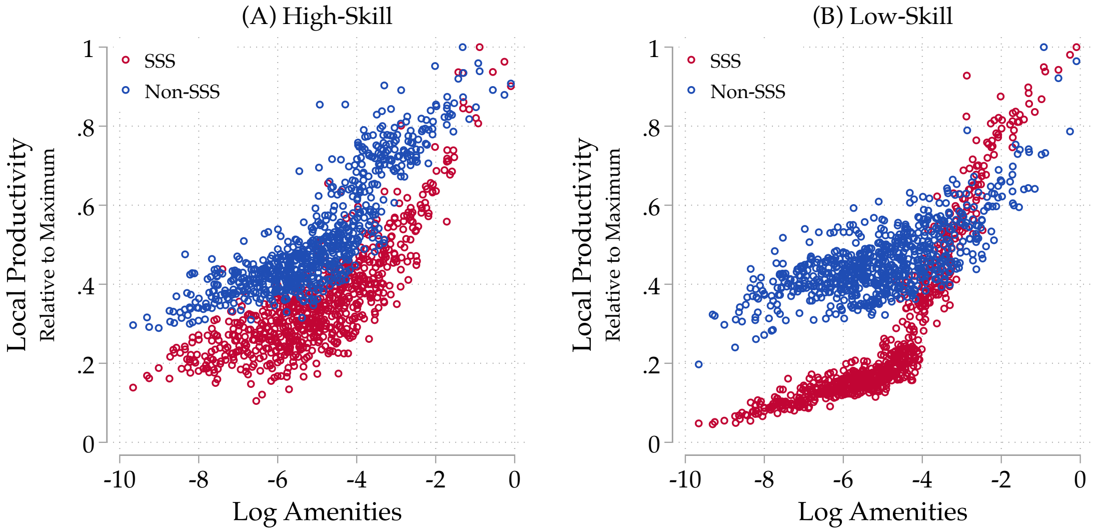
Notes: This figure plots average establishment size by commuting zone population in 1980, for both SSS (red) and Non-SSS (blue). Average establishment size is computed by dividing total employment in the sector and commuting zone by the count of establishments in the sector and commuting zone. The data 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-

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[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.

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

ONLINE APPENDIX FOR

SKILLED SCALABLE SERVICES:
THE NEW URBAN BIAS IN RECENT ECONOMIC GROWTH

BY FABIAN ECKERT, SHARAT GANAPATI, AND CONOR WALSH

March 2021

`FOR ONLINE PUBLICATION ONLY`

A. THE URBAN WAGE GRADIENT IN EQUILIBRIUM

Consider the special case of the model outlined in Section 3.3. Labor supply is given by

$$L_r^S = \mathcal{G} A_r w_r^{\kappa},$$

where as before, $\mathcal{G}$ is a general equilibrium constant, and labor demand is given by

$$L_r^D = B_r(p^K) w_r^{\frac{1}{\gamma - 1}},$$

where $\gamma < 1$. $B_r(p^K)$ is a local labor demand shifter which incorporates the effect of the ICT capital price on entry decisions N_r and average firm productivity $\bar{Z}_r$, as well as the effect of location productivity α_r. For illustration we ignore the dependence of B_r on w_r, but the arguments below continue to hold when this is incorporated.

Taking the logarithm of these two equations and imposing that $L_r^D = L_r^S$ for all locations r gives

$$\log(w_r) = \frac{1}{\kappa}\log(B_r) + \frac{1}{\kappa}\frac{1}{\gamma - 1}\log(w_r) - \frac{1}{\kappa}\log(A_r) - \frac{1}{\kappa}\log(\mathcal{G})$$

and solving for w_r leaves us with

$$\log(w_r) = c_1 \log(B_r) - c_1 \log(A_r) - c_1 \log(\mathcal{G}) \tag{OA.1}$$

where $0 < c_1 = \frac{(1-\gamma)}{(1-\gamma)\kappa + 1} < 1$. Let $\tilde{x}_r$ denote the demeaned log version of a variable x_r such that

$$\tilde{x}_r \equiv \log(x_r) - \sum_{r=1}^{R} \log(x_r)/R$$

The urban wage gradient in the model-generated data can be defined as a regression of equilibrium demeaned log wages on demeaned log employment, as in

$$\beta_w = \frac{\sum_{r=1}^R \tilde{w}_r \tilde{L}_r}{\sum_{r=1}^R \tilde{L}_r^2}$$

Use (OA.1) to write this as

$$\begin{aligned}
\beta_w &= \frac{\sum_{r=1}^R \left(c_1 \tilde{B}_r - c_1 \tilde{A}_r\right)\left(\kappa c_1 \tilde{B}_r + (1-\kappa c_1)\tilde{A}_r\right)}{\sum_{r=1}^R \left(\kappa c_1 \tilde{B}_r + (1-\kappa c_1)\tilde{A}_r\right)^2} \\
&= \frac{\sum_{r=1}^R \kappa c_1^2 B_r^2 + (c_1(1-\kappa c_1) - \kappa c_1^2)\sum_{r=1}^R \tilde{B}_r \tilde{A}_r - c_1(1-\kappa c_1)\sum_{r=1}^R \tilde{A}_r^2}{\sum_{r=1}^R \kappa^2 c_1^2 \tilde{B}_r^2 + 2\kappa c_1(1-\kappa c_1)\sum_{r=1}^R \tilde{B}_r \tilde{A}_r + (1-\kappa c_1)^2 \sum_{r=1}^R \tilde{A}_r^2}
\end{aligned}$$

Note that as $\sum_{r=1}^R \tilde{B}_r^2$ grows large relative to the other terms, β_w approaches the inverse labor supply elasticity, such that variations in labor demand trace out the supply curve. When $\sum_{r=1}^R \tilde{A}_r^2$ becomes large, β_w approaches $\gamma - 1$, which is the inverse labor demand elasticity.

Using this expression, it can be shown that β_w decreases in the capital price p^K if and only if

$$\begin{aligned}\text{(OA.2)}\qquad & \left(\kappa c_1^2 \frac{d\sum_{r=1}^R \tilde{B}_r^2}{dp} + (c_1(1-c_1) - \kappa c_1^2) d \frac{\sum_{r=1}^R \tilde{B}_r \tilde{A}_r}{dp^K}\right) \\ & - \left(\kappa^2 c_1^2 \frac{d\sum_{r=1}^R \tilde{B}_r^2}{dp^K} + 2\kappa c_1(1-\kappa c_1) \frac{d\sum_{r=1}^R \tilde{B}_r \tilde{A}_r}{dp^K}\right)\beta < 0\end{aligned}$$

If $\beta\kappa < 1/2$, which is the empirically relevant case, then using (OA.2), $\frac{d\beta}{dp^K} < 0$ if the variance of labor demand decreases in p^K, and the covariance between $\tilde{B}_r$ and $\tilde{A}_r$ decreases in p.[51] Given the model mechanism we have presented, the first is always true. The second is true if there is an initial positive covariance between α_r and $\tilde{A}_r$, such that places with both high location productivity and desirable amenities see the greatest investment as p^K falls.

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[51] In the data, in most countries, $\beta_w \approx 0.1$. Most estimates of the spatial wage elasticity the authors are aware of are less than 5.

B. NON-HOMOTHETIC PRODUCTION

B.1 Modelling Skill-biased Technological Change

Several papers model a form of technological progress that is potentially biased towards one type of workers and not another. Consider a set up with two types of workers, high- and low-skill. The canonical paper on skill-biased technical progress by Krusell et al. (2000) (along with subsequent work) postulates a homothetic CES production function in which capital complements high-skill workers:

$$y_f = \left((k_f^{\frac{\epsilon-1}{\epsilon}} + \alpha h_f^{\frac{\epsilon-1}{\epsilon}})^{\frac{\epsilon}{\epsilon-1}\frac{\sigma-1}{\sigma}} + (1-\alpha) l_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{OA.3}$$

where $\epsilon < 1$ and $\sigma > 1$. Declines in the price of capital p^K increase capital adoption, and since capital is complementary with high-skill labor, this increases the demand for high-skill labor. With fixed aggregate labor supply, this induces movements in the skill premium as the capital price declines which are able to match the data under plausible parameterizations.

Another approach taken by Beaudry et al. (2010) does not model capital directly, and assumes that there are two different production functions available, that differ in the relative productivity of high-skill workers:

$$y_f = \left(\alpha_\tau h_f^{\frac{\sigma-1}{\sigma}} + (1-\alpha_\tau) l_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{OA.4}$$

where firms can now choose from a menu $\{\alpha_\tau\}_\tau$.

The advantage of the first approach is that skill-biased technical change occurs in terms of the observable quantity of equipment capital k. This allows for an intuitive approach to measurement. In addition, the production function parameterizes the strength of complementarity and hence the skill bias in one parameter ϵ. While this formulation works well in the aggregate to explain the skill *premium*, it is too rigid to produce the actual changes in wages observed across regions in the US. In particular, the production function cannot simultaneously produce the changing worker composition of the SSS sector in dense cities *and* the observed amounts of wage growth under reasonable parameterizations. We illustrate this with an example below.

The approach taken by Beaudry et al. (2010) on the other hand is less attractive to take to the data. There are many potential menus of $\{\alpha_\tau\}_\tau$ that could give rise to changes in the aggregate skill premium. Restricting technology choice to two technologies is nevertheless hard to square with many firms adopting different amounts of capital (see Figure 5). Furthermore, it is unclear how to use observed quantities and prices of ICT capital with this production technology in a consistent way.

We instead employ a structure that has much of the measurement advantages of the formulation by Krusell et al. (2000) but allows for some of the flexibility of changes in relative productivities afforded by Beaudry et al. (2010), albeit in a parametric way that maintains discipline.

$$y_f = (z_f(1+\mu_s k_f^{\beta}))^{1-\gamma}\left(\alpha y_f^{\frac{\epsilon^H}{\sigma\gamma}} h_f^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^L y_f^{\frac{\epsilon^L}{\sigma\gamma}} l_f^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma\gamma}{\sigma-1}}, \tag{OA.5}$$

Relative to the other formulations this production function allows for changing factor intensities as a function of overall firm output (or scale). As output increases the marginal product of high- and low-skill workers can either increase or decrease in absolute terms. This is flexible enough to lead to increases or decreases in the absolute number of high- and low-skill workers hired as firm-level output increases and hence allows to speak to the strong compositional changes in the workforce of SSS industries in the data. At the same time, ICT capital enters the production function and we can use the observed price and quantity of this type of capital to measure the importance of our mechanism in a disciplined and transparent way. Trottner (2019) and Lashkari et al. (2018) are two other recent papers that use this type of formulation to model skill-biased technical progress.

B.2 Krusell, Ohanian, Rios-Rull, and Violante (2000)

We now briefly discuss the difficulty of the production function in Krusell et al. (2000) (KORV) in accounting for the absence of low-skill wage growth in the face of declining technology prices. The homothetic CES production function in KORV in which capital is complementary with high-skill workers can be adapted to a spatial context by specifying:

$$y_f = \left((k_f^{\frac{\epsilon-1}{\epsilon}} + \alpha_{r,s}^H h_f^{\frac{\epsilon-1}{\epsilon}})^{\frac{\epsilon}{\epsilon-1}\frac{\sigma-1}{\sigma}} + \alpha_{r,s}^L l_f^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{OA.6}$$

where $\epsilon < 1$ and $\sigma > 1$, and where $\{\alpha_{r,s}^H, \alpha_{r,s}^L\}$ differ across regions and sectors. For simplicity, assume that all firms within an $\{r, s\}$ pair are identical and share this production function.

Substituting in the optimal choice of capital for a firm then yields

$$\begin{aligned} y_f &= \left(\left((\frac{p^K \alpha_{r,s}^H}{w_{r,s}^H})^{1-\epsilon} + \alpha_{r,s}^H\right)^{\frac{\epsilon}{\epsilon-1}} h_f^{\frac{\sigma-1}{\sigma}} + \alpha_{r,s}^L l_f^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \\ &= \left(\bar{\alpha}_{r,s}^H h_f^{\frac{\sigma-1}{\sigma}} + \alpha_{r,s}^L l_f^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \end{aligned} \tag{OA.7}$$

where we have defined $\bar{\alpha}_{r,s}^H \equiv \left((\frac{p^K \alpha_{r,s}^H}{w_{r,s}^H})^{1-\epsilon} + \alpha_{r,s}^H\right)^{\frac{\epsilon}{\epsilon-1}}$. Note that equation (OA.7) appears as a reduced form production function which only takes high- and low-skill labor as inputs, and parallels the function of Beaudry et al. (2010) in (OA.4). Given the complementarity between ICT capital and high-skill labor ($\epsilon < 1$), for a given wage $\frac{d\bar{\alpha}^H_{r,s}}{dp^K} < 0$, so that declines in the price of ICT capital appear as an increase in the productivity of high-skill labor in the reduced production function in (OA.7). The optimal ratio of high- to low-skill labor is given by

$$\text{(OA.8)} \qquad \frac{h_f}{l_f} = (\frac{\alpha^L_{r,s}}{\bar{\alpha}^H_{r,s}} \frac{w^H_{r,s}}{w^L_{r,s}})^{-\sigma}.$$

We can use this equation to think about the kind of skill-biased technical change required to rationalize movements in the skill premium across space. Write this in log changes as

$$\Delta \log\left(\frac{\bar{\alpha}^H_{r,s}}{\alpha^L_{r,s}}\right) = \frac{1}{\sigma}\Delta \log\left(\frac{h_f}{l_f}\right) + \Delta \log\left(\frac{w^H_{r,s}}{w^L_{r,s}}\right).$$

Movements in the capital price p^K only effect $\bar{\alpha}^H_{r,s}$, so we can hold $\alpha^L_{r,s}$ fixed. Now, take a concrete example, using the data in Table A.1. The ratio of high-skill to low-skill labor in New York and San Francisco (the densest decile) within SSS increased by a factor of 5.6, while the skill premium increased by a factor of 1.3. Taking the elasticity of substitution σ from Krusell et al. (2000) as 1.6, the required increase in $\bar{\alpha}^H_{r,s}$ is a factor of 4.05 over its 1980 value. Note also that to rationalize the original skill premium in 1980 in New York would require $\bar{\alpha}^H_{r,s} = 0.75\alpha^L_{r,s}$.

Now, substituting out the optimal ratio between high-skill and low-skill labor from (OA.8) yields

$$\begin{aligned} y_f &= \left(\bar{\alpha}^H_{r,s}(\frac{h_f}{l_f})^{\frac{\sigma-1}{\sigma}} + \alpha^L_{r,s}\right)^{\frac{\sigma}{\sigma-1}} l_f \\ &= \left((\bar{\alpha}^H_{r,s})^{\sigma}(\frac{w^H_{r,s}}{w^L_{r,s}})^{1-\sigma}(\alpha^L_{r,s})^{1-\sigma} + \alpha^L_{r,s}\right)^{\frac{\sigma}{\sigma-1}} l_f. \end{aligned}$$

With constant returns to scale, the wage of the low-skill workers in location r must be in equilibrium

$$w^H_{r,s} = p^s\left(\bar{\alpha}^H_{r,s}(\frac{H_{r,s}}{L_{r,s}})^{\frac{\sigma-1}{\sigma}} + \alpha^L\right)^{\frac{\sigma}{\sigma-1}}.$$

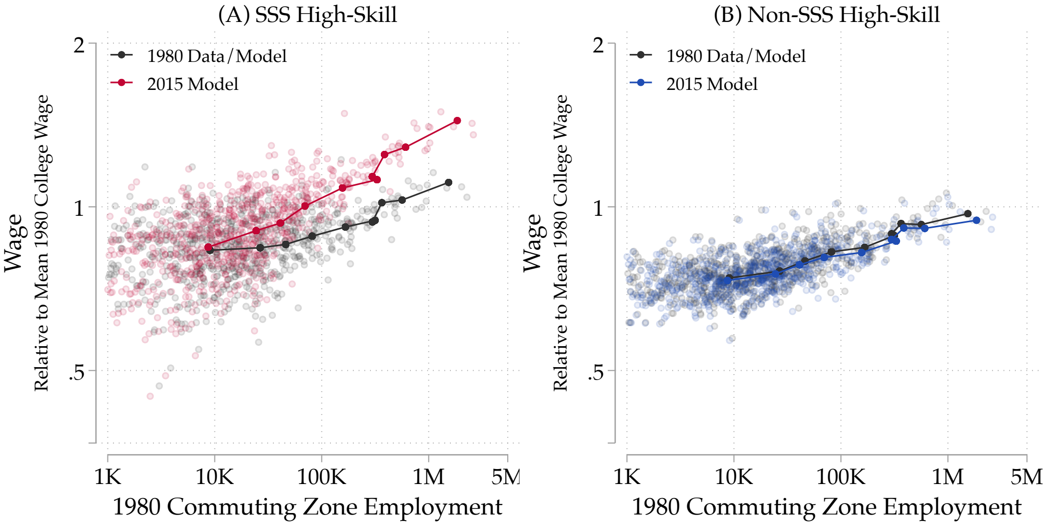
This is the key expression that shows the difficulty in using a homothetic model. Given that the skill ratio increased strongly within SSS in all areas, a decline in the capital price implies strong wage growth for the low-skill workers in SSS. Counterfactually strong, in fact. For example, using the observed change in the skill ratio and the implied increase in $\bar{\alpha}^H_{r,s}$, and without changes in sectoral prices we find that

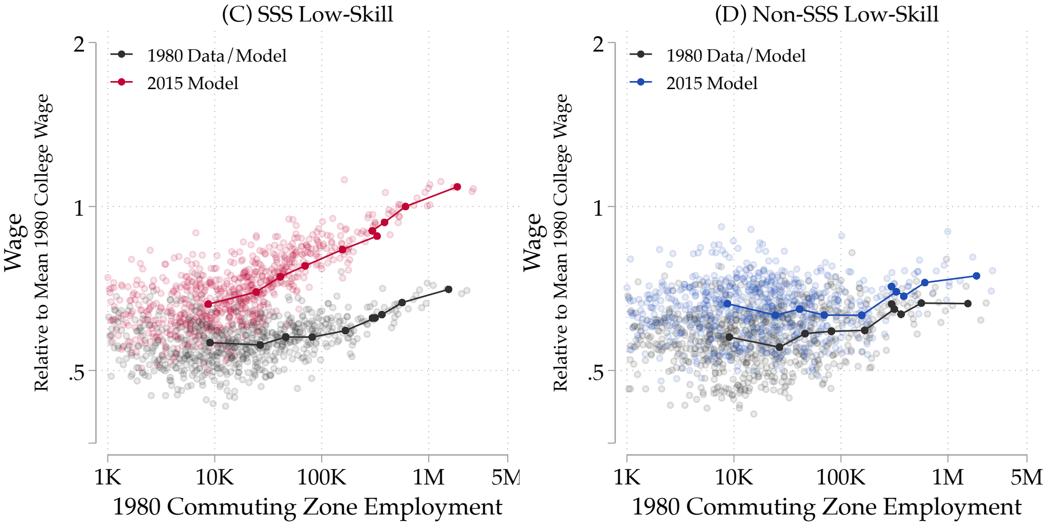
$$\frac{w^L_{\text{NY2015,SSS}}}{w^L_{\text{NY1980,SSS}}} = 26.4$$

This is, of course, at odds with the data. With moderate elasticities of substitution, the strong growth in the skill-ratio in dense cities within SSS creates strong demand pressures for low-skill labor, even if this growth fundamentally arises from technical change biased towards the high-skilled.

In our model, setting the non-homotheticity parameters to $\epsilon_H = \epsilon_L = 0$ means that ICT capital adoption is not skill-biased. We re-solve the model under this assumption and the same ICT price decline as in the paper. Figure OA.1 shows the resulting wage growth by sector and education group. Equilibrium wages rise strongly for the low-skill in SSS. In fact, due to the general skill-deepening of the U.S. economy between 1980 and 2015, and the resulting downward pressure on high-skill wages, the skill premium actually falls.

Figure OA.1: Wages in the Model in 1980 and 2015 Across Commuting Zones by Education Group and Sector Under Homotheticity





Notes: This figure plots commuting zone's wages against their population for the different sectors, education group, and years in the model under the assumption that $\epsilon_L = 0$. In the data, high-skill is mapped to college-educated workers and low-skill is mapped to non-college-educated workers. Scatter dots are individual commuting zones, with black representing the 1980 data from the ACES which is matched exactly in the model. Colored dots are the model predicts for 2015. Lines are the averages within the ten density decile groups used throughout the paper, for both 1980 and 2015.

C. SECTORAL AND LOCATION CHOICE PROBABILITIES

Consider first the sectoral choice of worker i who has chosen to live in location r and who knows his shock η_s^i for each sector s. Such a worker maximizes utility by solving:

$$\max_s \{w_{r,s}^e \times \eta_s^i\}.$$

In the paper, we assume that η_s^i is Fréchet distributed with inverse scale $D_{r,s}^e$ and shape parameter ϱ^e. The Frechet distribution is give by:

$$F(\eta) = \exp\left(D_{r,s}^e \times \eta^{-\varrho^e}\right).$$

We can then derive the fraction of workers who optimally choose sector s, conditional on having already chosen to live in location r. We use the aggregation properties of the Fréchet distribution:

$$\begin{aligned}
\mathrm{P}^e\left(s^* = s \mid r\right) &= \int_0^\infty \mathrm{P}^e(w_{r,s^*}^e \times \eta_{s^*}^i = o) \times \prod_{s' \neq s} \mathrm{P}^e(w_{r,s'}^e \times \eta_{s'}^i < o) do \\
&= \int_0^\infty -D_{r,s}^e \varrho^e o^{-\varrho^e - 1} (w_{r,s}^e)^{\varrho^e} \prod_s \exp\left(D_{r,s}^e o^{-\varrho^e} (w_{r,s}^e)^{\varrho^e}\right) do \\
&= \int_0^\infty -D_{r,s}^e \varrho^e o^{-\varrho^e - 1} (w_{r,s}^e)^{\varrho^e} \exp\left(o^{-\varrho^e} \sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}\right) do \\
&= \frac{D_{r,s}^e (w_{r,s}^e)^{\varrho^e}}{\sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}} \times \\
&\int_0^\infty -\varrho^e o^{-\varrho^e - 1} (\sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}) \exp\left(o^{-\varrho^e} \sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}\right) do \\
&= \frac{D_{r,s}^e (w_{r,s}^e)^{\varrho^e}}{\sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}} \times 1,
\end{aligned}$$

where s^* indicates the optimal sector choice.

Now, compute the probability density of the indirect utility of workers with skill e in location r conditional on choosing to work in sector s, denoted v_r^e:

$$\begin{aligned}
\mathrm{P}^e(v_r^e < o \mid s^* = s, r^* = r) &= \frac{1}{\mathrm{P}^e\left(s^* = s \mid r^* = r\right)} \times \\
&\int_0^\infty -\varrho^e o^{-\varrho^e - 1} (\sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}) \exp\left(o^{-\varrho^e} \sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}\right) do \\
&= \frac{\sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}}{D_{r,s}^e (w_{r,s}^e)^{\varrho^e}} \times \\
&\int_0^\infty -D_{r,s}^e \varrho^e o^{-\varrho^e - 1} (w_{r,s}^e)^{\varrho^e} \exp\left(o^{-\varrho^e} \sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}\right) do \\
&= \int_0^\infty -\varrho^e o^{-\varrho^e - 1} (\sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}) \exp\left(o^{-\varrho^e} \sum_s D_{r,s}^e (w_{r,s}^e)^{\varrho^e}\right) do,
\end{aligned}$$

where r^* indicates the optimal location choice.

This is again a Fréchet distribution with inverse scale parameter $\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e}$ and shape parameter ϱ^e. We use the formula for the mean of a Frechet distribution to derive an expression for the expected indirect utility of a worker of type e from working in sector s:

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

Note that $\bar{v}^e_r$ is not a function of the sector. As a result, it is not just the average utility of people who choose to work in sector s^* after choosing location r but that of any type e worker conditional on moving to r independent of the sector they will choose upon arrival. This property of the Fréchet distribution is discussed in Eaton and Kortum (2002).

When making a location decision workers take into account the expected real wage they can earn in each location, and their location specific amenity. As a result:

$$r^* = \arg\max_r \{\bar{v}^e_r \times \eta_r\}$$

Following the above derivation of the fraction of workers who choose to work in sector s we can derive an analytical expression for the fraction of workers who choose to live in location r:

$$\mathrm{P}^e\left(r^* = \arg\max_r \{\bar{v}^e_r \times \eta_r\}\right) = \frac{A^e_r(\bar{v}^e_r)^{\kappa^e}}{\sum_r A^e_r(\bar{v}^e_r)^{\kappa^e}}.$$

Analogously, we can derive the expected utility of a worker who has not yet chosen location and sector and has not yet drawn his idiosyncratic preference shocks:

$$\begin{aligned}
\bar{v}^e &= g\left(1 - \frac{1}{\kappa^e}\right) \times (\sum_r A^e_r(\bar{v}^e_r)^{\kappa^e})^{\frac{1}{\kappa^e}} \\
&= g\left(1 - \frac{1}{\kappa^e}\right) \times (\sum_r A^e_r g\left(1 - \frac{1}{\varrho^e}\right) \times (\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e})^{\frac{1}{\varrho^e}})^{\frac{1}{\kappa^e}} \\
&= g\left(1 - \frac{1}{\kappa^e}\right) \times \Gamma\left(1 - \frac{1}{\varrho^e}\right) \times \sum_r A^e_r \times (\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e})^{\frac{1}{\varrho^e \kappa^e}},
\end{aligned}$$

where $\bar{v}^e$ is also the average welfare of a type e individual in the model. Here $g(\cdot)$ denotes the Gamma Function.

Next we compute the spatial labor supply elasticity with respect to the local wage. First, we re-write the location choice:

$$\begin{aligned}
\mathrm{P}^e\left(r^* = \arg\max_r \{\bar{v}^e_r \times \eta_r\}\right) &= \frac{A^e_r(g\left(1 - \frac{1}{\varrho^e}\right) \times (\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e})^{\frac{1}{\varrho^e}})^{\kappa^e}}{\sum_r A^e_r(g\left(1 - \frac{1}{\varrho^e}\right) \times (\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e})^{\frac{1}{\varrho^e}})^{\kappa^e}} \\
&= \frac{A^e_r(\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e})^{\frac{\kappa^e}{\varrho^e}}}{\sum_r A^e_r(\sum_s D^e_{r,s}(w^e_{r,s})^{\varrho^e})^{\frac{\kappa^e}{\varrho^e}}}
\end{aligned}$$

Now consider a shock to wages in location r in both sectors that raises them by a factor of λ. For small such shocks and given that we have a large number of regions in our application we obtain:

$$\frac{d \log \mathrm{P}^e \left(r^* = \arg\max_r \{\bar{v}_r^e \times \eta_r\}\right)}{d \log \lambda} \approx \kappa^e \tag{OA.9}$$

The exact same elasticity is denoted β^w in Diamond (2016) is estimated to be 3.261 for non-college, and 4.976 for college-educated, non-black, non-immigrant workers. We use these estimated elasticities in our application.

D. DATA PROCESSING DETAILS

D.1 Defining Commuting Zones

We largely follow Autor and Dorn (2013) in assigning counties to 1990 USDA ERS commuting zones as constructed by Tolbert and Sizer (1996). However there are 11 counties that change or are added over our time period that we need to assign to a commuting zone. We merge these counties with adjacent counties or their precursor counties. In particular, we combine Federal Information Processing Standards (FIPS) Codes 12025 with 12086, 08014 with 08013, 51780 with 51083, 30113 with 56029 02231 with 02282, 02105 with 02282, 02230 with 02282, 02195 with 02280, 02275 with 02280, 02275 with 02280, and 02198 with 02201.[52]

In general, these are minor adjustments, with only the first three being associated with substantial population counts (the first is a subdivision of Miami-Dade county, the second involves the creation of a new county in the Denver-Boulder Metro Area, the third involves a minor subdivison of Halifax County, Virginia). The last seven adjustments all involve a complete reordering of extremely remote Alaskan commuting zones primarily in the Wrangell area. We do not use Alaskan commuting zones in our counterfactual analysis or model calibration.

D.2 Price Index Data

All prices are relative to the BLS Consumer Price Index for Urban Consumers (CPI-U) corresponding to the FRED series CPIAUCSL. For BEA asset prices, we download the following series from the FRED database:

- Y033RG3Q086SBEA
- Y034RG3Q086SBEA
- A680RG3Q086SBEA
- A681RG3Q086SBEA
- A862RG3Q086SBEA
- Y001RG3Q086SBEA
- Y006RG3Q086SBEA
- Y020RG3Q086SBEA
- B985RG3Q086SBEA
- Y020RG3Q086SBEA

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[52] Combining 30113 with 56029 is the only cross-state merge, attributing remote parts of Yellowstone National Park to Park County, WY.

We report these series relative to the BLS Consumer Price Index for all urban consumers.

D.3 QCEW Processing

For some of our aggregate wage and employment statistics, we use the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). Unlike the Census LBD, this product is public-use, but also covers most of the U.S. workforce using administrative records. However the data from 1980-1990 is not directly comparable to data after 1990. In particular, the QCEW uses the SIC industry classification standard before 1990. To convert this to the modern NAICS industry standard we use the Fort and Klimek (2016) crosswalks to the NAICS 2012 classification for the SIC 1977 codes for data from 1980-1986 and the SIC 1987 codes for 1987-1990. We make two small adjustments: we classify "SIC 1520" as a Non-SSS industry and "SIC 9999" (non-classifiable establishments) as a Non-SSS industry.

D.4 Industry Misreporting in Decennial Census and American Community Survey

Data from the QCEW and LBD datasets use administrative records; the first using records collected from unemployment insurance filings and the second using data from tax records. In general, these two data sets closely track each other in terms of aggregate wage and employment growth. However, there are some discrepancies between them on the one side and the self-reported data from the Decennial Census and the ACS on the other side. In Figures OA.2a and OA.2b we plot average wages and total employment over time for SSS and Non-SSS in all three data sets. Figures OA.2c and OA.2d also plot wages and employment growth across the groups of commuting zones used throughout the paper.

In particular, there appears to be a much lower employment count for SSS and a more muted wage premium in the public Census data. We hypothesize that individuals are reporting their firm's sectoral classification, rather than their establishment's sectoral classification.

We explore this possibility in a case study of Fayetteville (AR) commuting zone, which includes the Bentonville headquarters and support facilities of the largest American retailer, Walmart.[53] In the 2015 QCEW, using administrative records, retail accounts for 12% of employment in the Fayetteville, AR metro area. This is broadly in line with the national average, which stands at 11% in the same dataset. Wages are also broadly in line, with retail workers in Fayetteville making 10% less than the national average for retail workers, and making 45% less than the average worker across industries in Fayetteville.[54] The data for Fayetteville looks very different in the self-reported ACS sample

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[53] We will only use public-use data from the QCEW here to maintain privacy of tax records from the LBD. The Fayetteville (AR) commuting zone contains both the towns of Fayetteville and Bentonville.

[54] Note, the QCEW suppresses the statistics for "Management of companies and enterprises" in the Fayet-

for 2015. In the Fayetteville CZ, retail accounts for 20% of employment, double the national average. Wages in Fayetteville retail are 45% higher than retail workers in the rest of the nation, and 30% higher than all other workers in Fayetteville. Also retail shows a disproportionately high college and post-graduate share of employment, with a lot of workers in legal, accounting, and management roles.

This provides evidence for our hypothesis that workers are using their firm's industry (retail for Walmart), rather than their establishment (corporate headquarters for Walmart).

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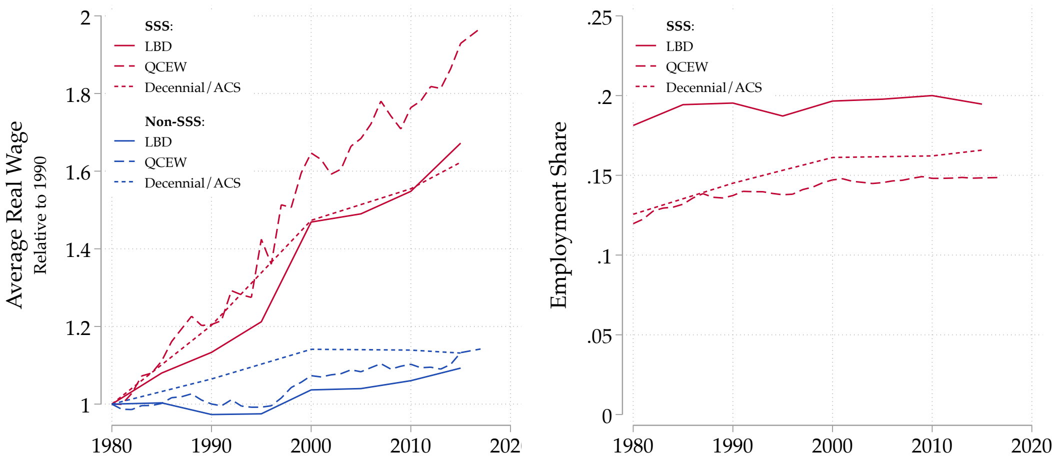
teville area as it would effectively reveal the average wage for a single firm or establishment.

FIGURE OA.2: COMPARING SKILLED SCALABLE SERVICES WAGE GROWTH ACROSS DATA SETS

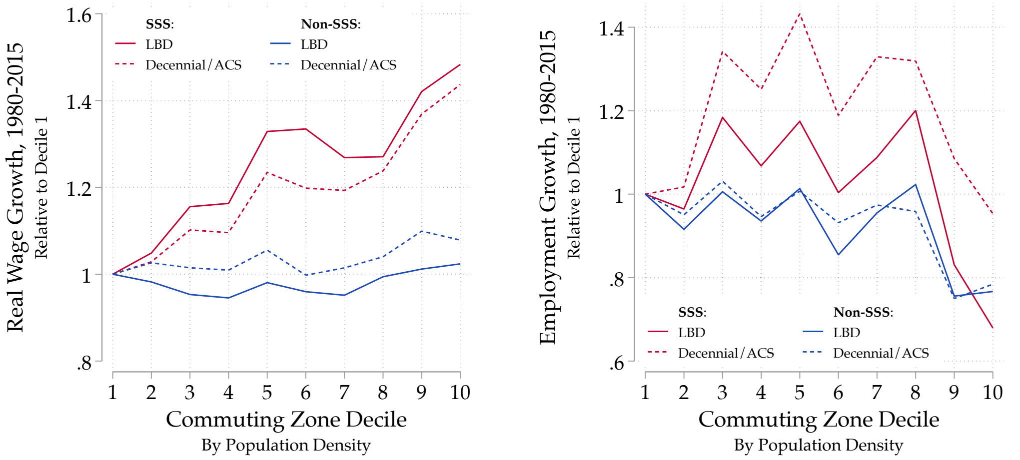
(A) Aggregate Wages

(B) Aggregate Employment



(C) Wages Across Commuting Zones

(D) Employment Across Commuting Zones



Notes: This is a comparison of four administrative and survey data sources, the Longitudinal Business Database (LBD), the Quarterly Census of Employment and Wages (QCEW) and the combined Decennial Census (Decennial) and American Community Survey (ACS). Panel (A) highlights different wages across SSS and non-SSS sectors over time. Panel (B) highlights the employment share of the SSS sector over time. Panels (C) and (D) highlights the spatial wage gradient change and employment change for both sectors from 1980-2015 for the LBD and the Decennial/ACS Data. Non-censored QCEW data is unavailable spatially due to disclosure risk.

E. ADDITIONAL FIGURES

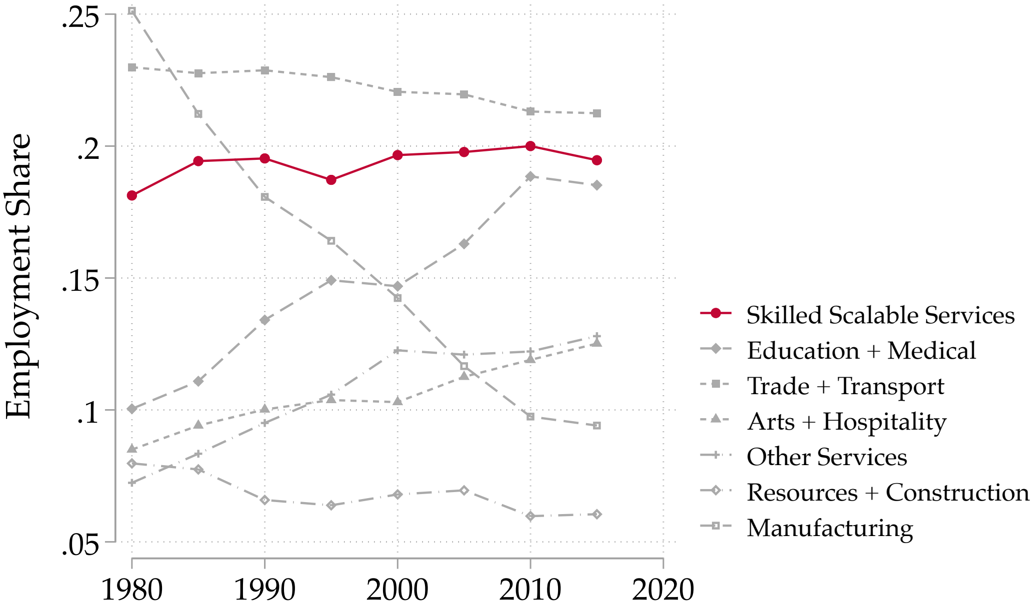
Figure OA.3 shows the fraction of employment accounted for by each 2-digit NAICS industry over time. Skilled Scalable Services have seen only minor employment share growth since 1980.

Figure OA.4 shows average wage growth by sector plotted against commuting zone population density. It shows the strong urban-biased wage growth in SSS industries, and the almost insignificant urban bias in the non-SSS wage growth.

Figure OA.5 shows wages for medical doctors and SSS workers with at least a college degree, and all other workers with at least a college degree ("Other Degree Holders"). While the wage-density gradient has remained almost entirely constant for doctors and other college degree holders outside SSS, it has increased dramatically for SSS workers. The wage-density gradient for doctors is negative. This highlights the difference between scalable and non-scalable skilled service industries.

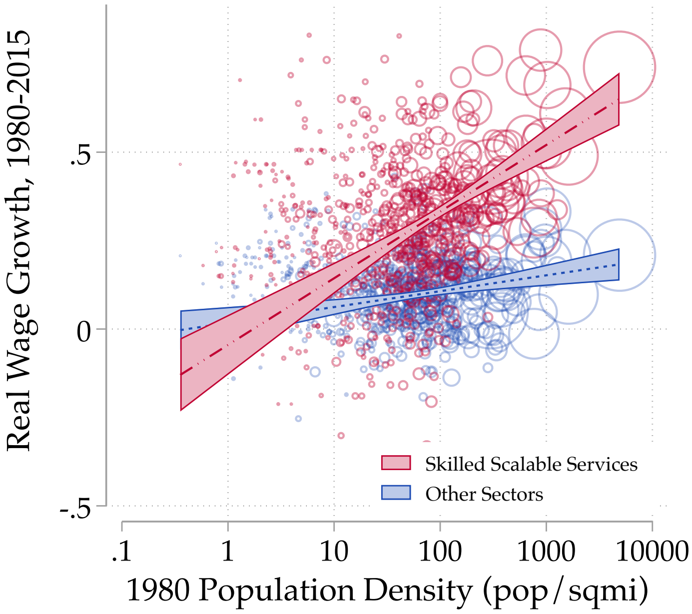
Figure OA.6 replicates Figure 9 in the paper when we instead assume that sectoral prices are fixed at their 1980 values.

FIGURE OA.3: SECTORAL EMPLOYMENT SHARES



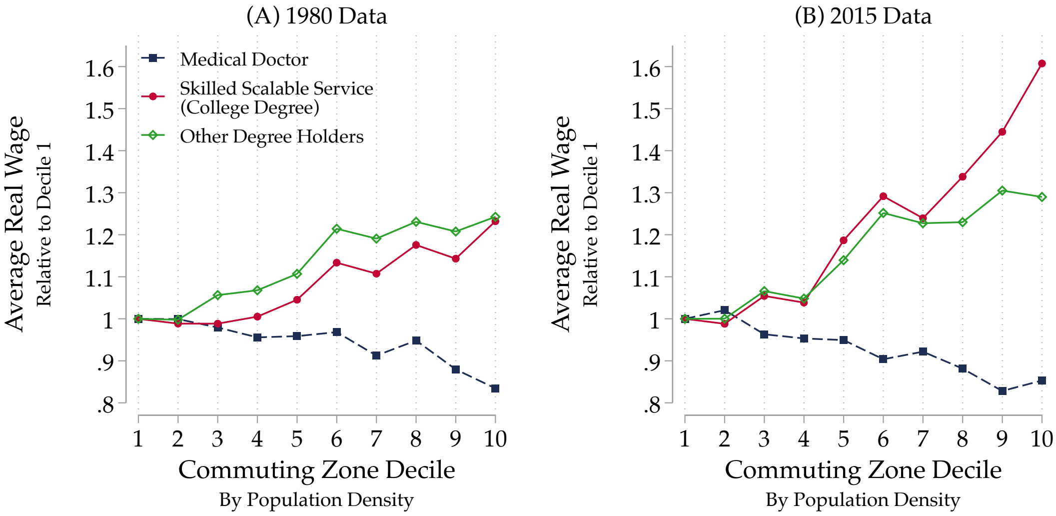
Notes: This figure plots employment shares by year and major industry grouping. The data are from the LBD.

FIGURE OA.4: AVERAGE WAGE GROWTH ACROSS COMMUTING ZONES BY SECTOR



Notes: This figure plots the growth in the average wage in at the sector and commuting zone level between 1980 and 2015. Size of circles is 1980 population. Alaskan commuting zones are omitted. The data are from the Decennial Census (1980) and the ACS (2015). The data are from the Decennial Census (1980) and the ACS (2015).

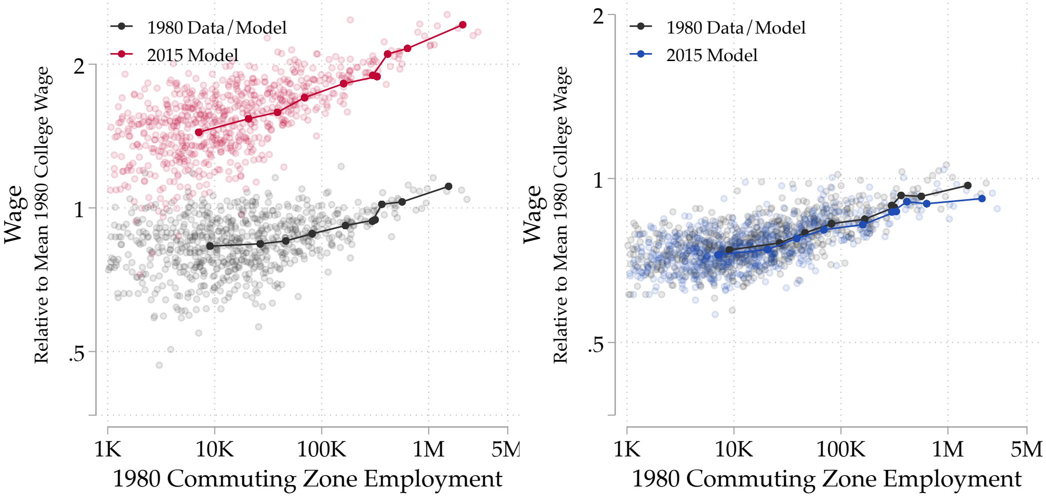
FIGURE OA.5: AVERAGE WAGES ACROSS COMMUTING ZONES BY OCCUPATION GROUP



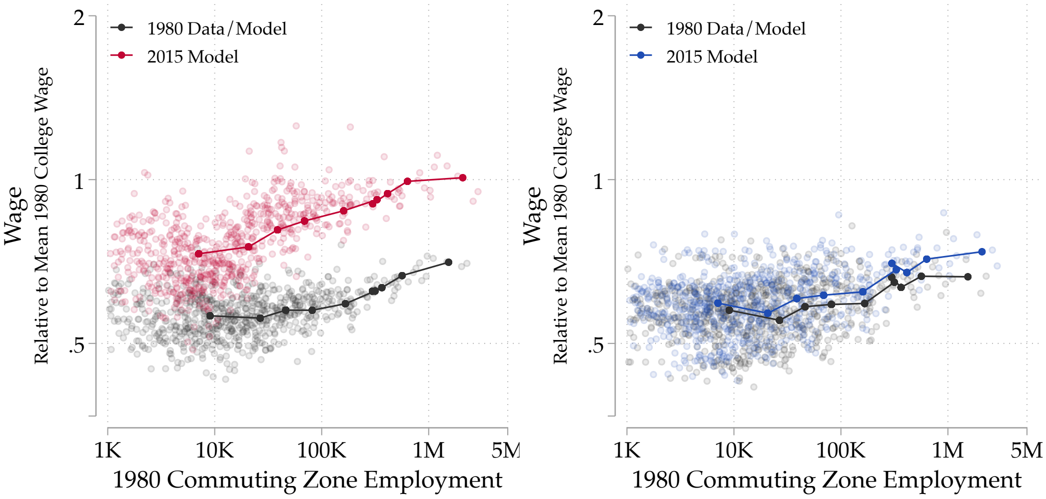
Notes: This figure plots average wage growth by commuting zone density decile for Medical doctors, SSS workers with a college degree, and all other non-SSS college degree holders (including graduate degrees). The data are from the Decennial Census and the ACS, adjusted by the BLS CPI-U.

Figure OA.6: Wages in the Model with Fixed Sectoral Prices in 1980 and 2015 Across Commuting Zones by Education Group and Sector

(A) SSS High-Skill (B) Non-SSS High-Skill



(C) SSS Low-Skill (D) Non-SSS Low-Skill



Notes: This figure plots commuting zone's wages against their population for the different sectors, education group, and years in the model under the assumption sectoral prices p^N and p^S are fixed. In the data, high-skill is mapped to college-educated workers and low-skill is mapped to non-college-educated workers. Scatter dots are individual commuting zones, with black representing the 1980 data from the ACES which is matched exactly in the model. Colored dots are the model predicts for 2015. Lines are the averages within the ten density decile groups used throughout the paper, for both 1980 and 2015.

F. INDUSTRIES, OCCUPATIONS, OR EDUCATION?

A large recent literature focuses on the role of occupations in employment polarization in the United States (see Autor and Dorn (2013)). Papers in this literature often categorize occupations by their task content. We follow Jaimovich and Siu (2020) and Rossi-Hansberg et al. (2019) in classifying occupations into cognitive non-routine occupations (CNR) and others (non-CNR). CNR occupations are typically high-skill occupations that require cognitive non-routine abilities. The left panel of Figure A.7 shows wage growth across U.S. commuting zones ordered by their density in 1980, separately for workers in CNR and non-CNR occupations. CNR wages did grow faster in denser locations. But the figure also reveals that CNR and non-CNR occupations *not* in the SSS sector exhibit wage growth that is largely unbiased across space. On the other hand all occupations within the SSS sector experienced wage growth strongly biased towards denser labor markets. The figures suggests that the density-bias in CNR wage growth is driven by the fact that SSS industries employ a disproportionate amount of CNR workers, but is not particular to CNR occupations.

Similarly, the bias in recent wage growth towards dense location may reflect something about education. Recent papers (e.g., Giannone (2017) and Rubinton (2019)) argue that the disproportionately fast growth of skilled wages in many large urban areas is due to faster skill-biased technical change in such cities. The right panel of Figure A.7 shows that indeed growth in wages for college-educated workers has exhibited a stronger density bias than growth in non-college wages. However, once we condition on the SSS sector we see that this is driven almost entirely by compositional differences: both college and non-college wages in SSS exhibit a strong bias towards denser labor markets, while not much of a bias exists for wages of these groups outside SSS. The reason skilled wages have seen faster growth in denser areas is their over-representation in the SSS sector, it is however not specific to skilled workers per se.[55]

Figure OA.5 shows average wages across commuting zones for medical doctors and for college-educated SSS workers for comparisons in 1980 and 2015.[56] Comparing the two panels shows that there is no density wage premium for doctors in either year, and that there was no markedly faster wage growth in denser locations for doctors either. Both of these facts stand in stark contrast to (college-educated) SSS workers.

We use data from the Decennial Census and ACS to look at wage differences within occupations (defined at the 6-digit SOC code level). For every commuting zone, educational group, year, SSS classification, 6-digit occupational code, we regress real wages on a SSS dummy and an SSS dummy interacted with CZ density, controlling for a full set of interactions between, occupations, educational groups, and CZ. We weight the regressions by the number of employees within each cell. The results are presented in Table OA.1.

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[55] Figure A.7 also shows the disappearance of the low-skill urban wage premium documented in Autor (2019): non-college workers experienced negative wage growth in some of the densest local labor markets (deciles 6,7, and 8).

[56] Medical doctors have a college degree by definition.

Column (1) shows the results without interacted fixed effects and Column (2) interacts all the fixed effects.[57] In 1980, there was no aggregate wage premium within occupation codes for SSS. By 2015, the wage premium ranged between 10,000 and 12,000 within a the same city, educational, group, and 6-digit SOC occupational code. Column (3) interacts this wage premium with CZ density in 1980 (scaled between 0 and 1). In particular, we find that the entirety of the SSS wage premium within jobs is driven by the densest CZ, with no difference for the least dense CZ. Further analysis reveals wide variation in wages driven by the large number of employees as "Managers and administrators," "Chief executives and public administrators," "Accountants and auditors," and "Office supervisors."

In summary, the evidence in this section suggests that the recent changes in the economic geography of wage growth are indeed driven by the SSS sector, rather than certain skill or occupational groups.

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[57] The number of observations decreases due to the number of singleton cells.

TABLE OA.1: REAL WAGES DIFFERENCE WITHIN OCCUPATION

	(1) Real Wage	(2) Real Wage	(3) Real Wage
1980 × SSS	-2022.2	1035.2	36.72
	(1410.8)	(386.3)	(486.1)
1990 × SSS	3048.6	3506.4	188.2
	(953.7)	(708.1)	(694.0)
2000 × SSS	8679.6	6186.1	362.1
	(1213.7)	(891.6)	(787.9)
2010 × SSS	9900.3	7878.0	-961.3
	(1314.4)	(1233.5)	(1057.0)
2015 × SSS	12156.7	9849.0	388.2
	(1162.2)	(1213.5)	(1209.0)
1980 × SSS × CZ Population Density			1520.6
			(414.9)
1990 × SSS × CZ Population Density			5100.0
			(492.8)
2000 × SSS × CZ Population Density			9093.1
			(1201.5)
2010 × SSS × CZ Population Density			13510.0
			(1793.8)
2015 × SSS × CZ Population Density			14432.2
			(2199.3)
Constant	56673.8	62684.2	62662.1
	(123.8)	(171.9)	(169.3)
Observations	2820287	895456	895456
R^2	0.666	0.913	0.914
FE: Yr, Occupation, Education, CZ	✓		
FE: Yr x Occupation x Education x CZ		✓	✓

Notes: Robust standard errors in parentheses. Observations are at a sector-commuting zone-6 digit SOC occupational code- educational (HS or less, Some College, College, or Graduate Degree)-commuting zone cell. Commuting zone density decile scaled from 0 to 1, with 0 representing the least dense commuting zones. The data are from the Decennial Census and the ACS, adjusted by the BLS CPI-U.

G. COMPUTATIONAL ALGORITHM

Solving for a spatial equilibrium with non-homothetic CES production poses some computational challenges. Firm-level output is only defined implicitly, and a non-linear equation must be solved each time to compute it. Solving the problem of the firm in equilibrium for firms in different locations (where wages are equilibrium objects) becomes burdensome with a large number of locations.

To deal with this computational challenge, we solve the problem of the firm over a 3-dimensional state space $\{z, w^H, w^L\}$ for fundamental firm-level efficiency, local high-skill wages and local low-skill wages. We then compute labor demands with this value function in each location for a given vector of wages, and then iterate on this vector until the labor market clears.

Using the optimality condition for low-skill labor, the firm's cost minimization problem for a level of output Y is

$$\begin{aligned} &\min_{\hat{h}_f} \frac{w^H_{r,s}}{\alpha^H_{r,s}}\hat{h}_f + \frac{w^L_{r,s}}{\alpha^L_{r,s}} y_f^{\frac{\epsilon^L-\epsilon^H}{\gamma}} \left(\frac{w^H_{r,s}\alpha^L_{r,s}}{w^L_{r,s}\alpha^H_{r,s}}\right)^{\sigma}\hat{h}_f \\ \text{s.t. } 1 &= \hat{z}_f^{1-\gamma}\left(y_f^{\frac{\epsilon^L-(\epsilon^H-\epsilon^L+1)(\sigma-1)}{\gamma\sigma}}\left(\frac{w^H_{r,s}}{w^L_{r,s}}\frac{\alpha^L_{r,s}}{\alpha^H_{r,s}}\right)^{\sigma-1} + y_f^{\frac{\epsilon^H-(\sigma-1)}{\gamma\sigma}}\right)^{\frac{\sigma}{\sigma-1}\gamma}\hat{h}_f^{\gamma} \end{aligned}$$

where $\hat{h}_f = h_f \alpha^H_{r,s}$. Solving this minimization problem yields optimal the high-skill labor demand of firm f, $\hat{h}_f$, as

$$\hat{h}_f(y_f) = \hat{z}_f^{\frac{\gamma-1}{\gamma}}\left(y_f^{\frac{\epsilon^L-(\epsilon^H-\epsilon^L+1)(\sigma-1)}{\gamma\sigma}}\left(\frac{w^H_{r,s}}{w^L_{r,s}}\frac{\alpha^L_{r,s}}{\alpha^H_{r,s}}\right)^{\sigma-1} + y_f^{\frac{\epsilon^H-(\sigma-1)}{\gamma\sigma}}\right)^{-\frac{\sigma}{\sigma-1}} \tag{OA.10}$$

We use this to then solve the output choice of the firm for given sectoral prices. The algorithm we use to compute a spatial equilibrium is as follows.

1. Guess a price for the non-SSS sector p^N, and compute p^S from

$$p^S = \left(1 - (p^N)^{1-\rho}\right)^{\frac{1}{1-\rho}}$$

2. First assume the firm does not adopt any ICT capital. For both sectors, guess an array of y^0 over the grid of the state space $\{z, w^H, w^L\}$, and and compute the partial derivative of the profit function as

$$\frac{\partial \pi}{\partial y} = p_s - w^H\frac{\partial \hat{h}}{\partial y}(y^0) - w^L(y^0)^{\frac{\epsilon^L-\epsilon^H}{\gamma}}\left(\frac{w^H}{w^L}\right)^{\sigma}\frac{\partial \hat{h}}{\partial y}(y^0)$$

where $\hat{h}(y^0)$ is given in (OA.10), and where this is supressing the firm subscript f. Use this expression to update the guess for y^0 until $\frac{\partial \pi}{\partial y} = 0$. This gives associated output and input choices $\{y, h, l\}$ over the state space $\{z, w^H, w^L\}$. Importantly, note that local productivities $\alpha^e_{r,s}$ only appear multiplicatively with the local wage in each location, so are omitted from solving for the value function. They are reintroduced when computing labor demands by adjusting the equilibrium wage.

3. If the firm does adopt ICT capital, begin with a guess for K^0, and then repeat the step above to compute optimal $\{y, h, l\}$. The update h_0 from solving the optimality condition
   $$k + k^{1-\beta} - (p^K)^{-1} h \left(w^H + w^L (\frac{w^H}{w^L})^\sigma (y^0)^{\frac{\epsilon^L - \epsilon^H}{\gamma}} \right) \frac{1-\gamma}{\beta}$$
4. Compute profits under adoption and non-adoption including the fixed cost, and then max over adopt and non-adopt at each point in the state space. This gives policy functions over $\{z, w^H, w^L\}$.
5. Guess a vector of wages $\{w^H_{r,s}, w^L_{r,s}\}$ over R locations and 2 sectors, and define
   $$\{\hat{w}^H_{r,s}, \hat{w}^L_{r,s}\} = \{w^H_{r,s}/\alpha^H_{r,s}, w^L_{r,s}/\alpha^L_{r,s}\}$$
6. Integrate profits over the productivity distribution $G(z)$ in each location, and compute the number of firms in each sector and location from
   $$\tau N_{r,s}^{\frac{\zeta}{1-\zeta}} = \mathbb{E}_z[\Pi(\hat{z}, \hat{w}^H_{r,s}, \hat{w}^L_{r,s})]$$
7. Compute labor demands in each location from
   $$\begin{aligned} H^D_{r,s} &= N_{r,s}\mathbb{E}_z[\hat{H}(\hat{z}, \hat{w}^H_{r,s}, \hat{w}^L_{r,s})]/\alpha^H_{r,s} \\ L^D_{r,s} &= N_{r,s}\mathbb{E}_z[\hat{L}(\hat{z}, \hat{w}^H_{r,s}, \hat{w}^L_{r,s})]/\alpha^L_{r,s} \end{aligned}$$
8. Compute labor supply from
   $$\begin{aligned} H^S_{r,s} &= \frac{A^H_r (\bar{v}^H_r)^{\kappa^H}}{\sum_r A^H_r (\bar{v}^H_r)^{\kappa^H}} \bar{H} \\ L^S_{r,s} &= \frac{A^L_r (\bar{v}^L_r)^{\kappa^L}}{\sum_r A^L_r (\bar{v}^L_r)^{\kappa^L}} \bar{L} \end{aligned}$$
9. Iterate on the guess for wages until the labor market clears in each location.
10. Compute sectoral outputs from
    $$Y_s = \sum_r N_{r,s}\mathbb{E}_z[y(\hat{z}, \hat{w}^H_{r,s}, \hat{w}^L_{r,s})]$$
    and update the sectoral prices from
    $$\frac{Y^N}{Y^S} = (\frac{p^S}{p^N})^\rho$$

Iterate until the goods market clears.

SUPPLEMENTARY MATERIAL FOR

SKILLED SCALABLE SERVICES:
THE NEW URBAN BIAS IN RECENT ECONOMIC GROWTH

BY FABIAN ECKERT, SHARAT GANAPATI, AND CONOR WALSH

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A. LIST OF ALL COMMUTING ZONES IN OUR SAMPLE

In this section, we present a complete list of all commuting zones (CZ) in our sample. CZ are defined by Tolbert and Sizer (1996) by clustering counties together based on the strength of their observed commuting ties. As a result, not all CZ correspond to cities or MSA. We list the corresponding city or MSA where possible.

For each CZ, we show its 1980 population, the population density decile into which we allocate it, and wages in the SSS and non-SSS sector in 1980 and 2015. The underlying data is taken from the U.S. Decennial Census files for 1980, and the American Community Survey for 2015, both accessed via Ruggles et al. (2015).

TABLE SM.1: COMPLETE LIST OF COMMUTING ZONES AND AVERAGE WAGES BY SECTOR (2015 USD ’000)

					Wages (’1000)			
		Commuting Zone			Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
1	38300	Los Angeles-Long Beach-Anaheim, California	11,510,106	6	53	56	58	90
2	19400	New York–Newark–Jersey City, New York	10,621,244	10	50	62	60	126
3	24300	Chicago-Naperville-Elgin, Illinois	7,171,437	10	56	61	61	100
4	19600	New York–Newark–Jersey City, New Jersey	5,267,294	10	54	67	64	119
5	19700	Philadelphia-Camden-Wilmington, Pennsylvania	5,190,486	9	51	62	56	95
6	11600	Detroit-Livonia-Dearborn, Michigan	5,180,483	9	61	61	60	79
7	20500	Boston-Cambridge-Quincy, Massachusetts	4,457,165	9	49	69	57	113
8	37800	San Francisco–Oakland–Fremont, California	3,585,007	9	56	74	59	129
9	11304	Washington-Arlington-Alexandria, Virginia	3,333,528	8	57	71	63	109
10	20901	Hartford-West Hartford-East Hartford, Connecticut	3,107,564	8	53	65	61	124
11	32000	Houston-Baytown-Sugar Land, Texas	3,000,051	7	56	62	60	92
12	16300	Pittsburgh, Pennsylvania	2,781,748	8	53	58	55	78
13	15200	Cleveland-Elyria-Mentor, Ohio	2,663,368	9	53	56	56	77
14	39400	Seattle–Tacoma–Bellevue, Washington	2,560,096	5	56	66	55	103
15	7100	Miami-Fort Lauderdale-Pompano Beach, Florida	2,398,314	8	46	53	54	80
16	18000	Buffalo-Cheektowaga-Tonawanda, New York	2,368,543	7	52	55	49	69
17	11302	Baltimore-Towson, Maryland	2,173,989	9	51	65	56	92
18	21501	Minneapolis-St. Paul-Bloomington, Minnesota	2,168,282	7	55	64	56	88
19	24701	St. Louis, Missouri	2,144,726	7	51	56	55	82
20	9100	Atlanta-Sandy Springs-Marietta, Georgia	2,051,508	7	49	56	54	91
21	33100	Dallas-Plano-Irving, Texas	1,985,086	7	51	58	54	90
22	38000	San Diego-Carlsbad-San Marcos, California	1,861,846	8	51	60	54	90
23	37500	San Jose-Sunnyvale-Santa Clara, California	1,798,661	6	58	78	61	131
24	12701	Cincinnati-Middletown, Ohio	1,711,354	8	52	58	54	81
25	28900	Denver-Aurora, Colorado	1,640,393	5	53	61	56	91
26	35001	Phoenix-Mesa-Scottsdale, Arizona	1,637,173	3	50	54	52	72
27	6700	Tampa-St. Petersburg-Clearwater, Florida	1,613,600	8	43	50	48	72
28	37400	Sacramento-Arden-Arcade-Roseville, California	1,559,343	4	51	59	52	83
29	24100	Milwaukee-Waukesha-West Allis, Wisconsin	1,538,236	8	53	58	56	73
30	29502	Kansas City, Missouri	1,441,821	5	51	56	53	77
31	20401	Providence-New Bedford-Fall River, Rhode Island	1,421,795	9	46	59	54	79
32	3300	New Orleans-Metairie-Kenner, Louisiana	1,348,419	7	50	52	53	68
33	15900	Columbus, Ohio	1,314,435	6	49	56	53	81
34	38801	Portland-Vancouver-Beaverton, Oregon	1,286,210	6	53	61	54	79
35	14200	Indianapolis, Indiana	1,198,556	7	51	60	51	75
36	31301	San Antonio, Texas	1,165,214	4	42	49	46	65
37	12501	Dayton, Ohio	1,151,295	6	51	50	52	63
38	17700	Syracuse, New York	1,091,865	5	46	54	47	66

TABLE SM.1: Complete List of Commuting Zones and Wages (2015 USD)

					Wages (’1000)			
		Commuting Zone			**Non-SSS**		**SSS**	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
39	7000	Fort Lauderdale-Pompano Beach-Deerfield Beach, Florida	1,081,445	8	46	49	55	78
40	33000	Dallas–Fort Worth–Arlington, Texas	1,063,053	5	49	57	52	81
41	13101	Louisville, Kentucky	1,006,857	6	48	54	49	68
42	12200	Grand Rapids-Wyoming, Michigan	997,113	5	51	50	53	73
43	18600	Albany-Schenectady-Troy, New York	981,287	5	46	58	51	77
44	36100	Salt Lake City, Utah	959,893	3	51	55	53	71
45	5202	Memphis, Tennessee	948,345	6	46	50	50	68
46	19100	Lancaster, Pennsylvania	944,067	7	45	54	47	79
47	33803	Oklahoma City, Oklahoma	929,222	4	48	54	50	61
48	900	Charlotte-Gastonia-Concord, North Carolina	924,182	5	42	54	50	94
49	10700	Birmingham-Hoover, Alabama	907,587	5	48	51	52	82
50	37200	Fresno, California	897,213	2	47	49	52	63
51	19200	York-Hanover, Pennsylvania	895,011	6	46	51	48	62
52	16400	Youngstown-Warren-Boardman, Ohio	880,371	7	53	50	47	64
53	2000	Virginia Beach-Norfolk-Newport News, Virginia	872,161	7	44	51	49	69
54	5600	Nashville-Davidson–Murfreesboro, Tennessee	867,474	5	45	54	49	80
55	20600	Manchester-Nashua, New hampshire	861,217	5	44	61	47	87
56	19500	Edison, New Jersey	849,211	9	56	69	67	117
57	500	Greensboro-High Point, North Carolina	836,855	5	40	45	44	62
58	7400	Orlando, Florida	829,048	5	43	48	49	68
59	1701	Raleigh-Cary, North Carolina	824,284	4	42	56	44	90
60	13501	Toledo, Ohio	819,982	7	54	53	51	75
61	2400	Richmond, Virginia	795,892	5	46	55	49	87
62	18800	Scranton–Wilkes-Barre, Pennsylvania	782,304	5	41	50	45	61
63	30402	Tulsa, Oklahoma	769,610	3	50	51	53	67
64	34701	Honolulu, Hawaii	762,565	9	48	57	49	69
65	7600	Jacksonville, Florida	758,255	5	45	52	47	69
66	38901	Eugene-Springfield, Oregon	738,159	3	49	47	48	62
67	19300	Poughkeepsie-Newburgh-Middletown, New York	727,971	5	50	61	54	82
68	28202	Omaha-Council Bluffs, Nebraska	689,736	4	48	56	51	69
69	8300	Greenville, South Carolina	687,531	4	40	47	46	64
70	14900	Gary, Indiana	683,715	7	60	57	52	79
71	16500	Erie, Pennsylvania	675,901	4	46	45	44	56
72	3500	Baton Rouge, Louisiana	672,081	4	51	56	54	74
73	15000	Canton-Massillon, Ohio	670,035	5	50	50	48	57
74	20800	Springfield, Massachusetts	646,148	7	45	57	49	75
75	35100	Tucson, Arizona	637,588	1	47	50	49	64
76	13600	South Bend-Mishawaka, Indiana	632,176	6	49	51	50	61
77	31201	Austin-Round Rock, Texas	623,416	3	45	60	49	85
78	302	Knoxville, Tennessee	605,022	5	44	49	51	63
79	20100	Portland-South Portland, Maine	601,212	2	39	51	47	69
80	30601	El Paso, Texas	578,967	2	41	44	46	52
81	8100	Columbia, South Carolina	572,520	4	41	49	45	63
82	24400	Rockford, Illinois	571,093	4	52	50	50	56
83	23900	Peoria, Illinois	557,067	4	55	56	53	73
84	19000	Allentown-Bethlehem-Easton, Pennsylvania	551,052	8	49	56	53	84
85	11900	Saginaw-Saginaw Township North, Michigan	549,601	4	55	48	49	57
86	31600	McAllen-Edinburg-Pharr, Texas	537,811	4	37	45	43	44
87	37901	Las Vegas-Paradise, Nevada	532,509	1	48	49	54	68
88	34901	Albuquerque, New Mexico	523,268	1	46	48	55	71
89	100	Kingsport-Bristol, Tennessee	521,405	4	40	44	42	49
90	1400	Fayetteville, North Carolina	519,561	4	36	44	39	57
91	4200	Little Rock-North Little Rock, Arkansas	514,243	4	42	52	52	67
92	24000	Racine, Wisconsin	507,196	6	52	52	49	67

TABLE SM.1: Complete List of Commuting Zones and Wages (2015 USD)

		Commuting Zone			Wages (’1000)			
					Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
93	11001	Mobile, Alabama	502,814	3	46	49	47	71
94	27501	Des Moines, Iowa	500,160	4	49	55	50	76
95	14100	Fort Wayne, Indiana	492,705	4	49	48	50	69
96	4002	Shreveport-Bossier City, Louisiana	486,294	3	45	51	46	51
97	3800	Lafayette, Louisiana	476,339	3	49	55	52	79
98	38601	Spokane, Washington	471,470	2	50	53	48	69
99	12100	Kalamazoo-Portage, Michigan	466,552	5	52	54	49	66
100	8202	Charleston-North Charleston, South Carolina	462,122	4	43	53	46	69
101	22500	Appleton, Wisconsin	460,060	4	49	53	49	62
102	23100	Madison, Wisconsin	459,186	3	49	58	47	89
103	19800	Wilmington, Delaware	458,545	8	53	60	49	73
104	32100	Beaumont-Port Arthur, Texas	457,875	3	54	55	51	60
105	3003	Jackson, Mississippi	455,328	3	42	47	49	58
106	38200	Santa Barbara-Santa Maria-Goleta, California	454,129	3	50	55	51	94
107	29301	Wichita, Kansas	453,536	3	48	51	49	59
108	16200	Johnstown, Pennsylvania	447,911	4	46	48	45	53
109	14000	Anderson, Indiana	447,760	5	48	46	44	55
110	37000	Modesto, California	445,493	2	47	50	50	72
111	31700	Corpus Christi, Texas	441,121	2	45	49	47	74
112	6401	Chattanooga, Tennessee	440,230	5	45	49	47	64
113	2500	Virginia Beach-Norfolk-Newport News, Virginia	433,851	6	44	51	49	72
114	6900	Sarasota-Bradenton-Venice, Florida	428,195	5	41	47	49	63
115	10900	Pensacola-Ferry Pass-Brent, Florida	421,002	4	42	49	46	61
116	1302	Myrtle Beach-Conway-North Myrtle Beach, South Carolina	420,248	3	37	45	43	56
117	11700	Lansing-East Lansing, Michigan	419,750	6	54	54	51	62
118	12901	Lexington-Fayette, Kentucky	416,563	4	45	53	49	72
119	16600	Roanoke, Virginia	414,297	4	42	48	46	68
120	23801	Davenport-Moline-Rock Island, Iowa	411,424	4	55	55	52	77
121	1900	Jacksonville, North Carolina	411,104	3	38	45	38	73
122	8401	Augusta-Richmond County, Georgia	410,168	3	40	48	42	64
123	15100	Cleveland-Elyria-Mentor, Ohio	409,172	7	52	50	50	69
124	37100	Bakersfield, California	403,089	2	51	50	53	66
125	37700	Santa Rosa-Petaluma, California	402,785	2	51	60	53	96
126	23500	Champaign-Urbana, Illinois	389,856	3	49	54	48	63
127	6000	Huntsville, Alabama	389,855	4	46	49	51	72
128	6800	Lakeland-Winter Haven, Florida	389,535	4	41	41	47	63
129	401	Winston-Salem, North Carolina	389,277	5	42	50	48	71
130	16901	Charleston, West Virginia	385,661	4	50	49	48	56
131	24900	St. Louis, Illinois	371,363	4	51	51	47	72
132	2700	Gulfport-Biloxi, Mississippi	368,811	3	43	46	46	49
133	14700	Evansville, Indiana	368,682	4	49	52	46	55
134	17100	Huntington-Ashland, West Virginia	362,367	4	49	48	46	54
135	9600	Anniston-Oxford, Alabama	362,181	3	39	48	45	63
136	28401	Colorado Springs, Colorado	347,662	3	47	52	49	76
137	18100	Corning, New York	342,617	3	45	55	44	63
138	800	Charlotte-Gastonia-Concord, North Carolina	342,162	5	37	46	43	79
139	22700	Wausau, Wisconsin	333,228	2	47	48	51	58
140	7300	Palm Bay-Melbourne-Titusville, Florida	332,855	6	46	47	52	72
141	14500	Lafayette, Indiana	330,285	3	46	48	47	57
142	17400	Hagerstown-Martinsburg, Maryland	327,345	4	44	52	44	62
143	8900	Macon, Georgia	322,858	3	43	48	43	54
144	16000	Mansfield, Ohio	321,912	4	47	45	46	58
145	7500	Deltona-Daytona Beach-Ormond Beach, Florida	320,224	4	41	43	43	65
146	29700	Springfield, Missouri	317,508	2	41	46	46	50

TABLE SM.1: Complete List of Commuting Zones and Wages (2015 USD)

	Commuting Zone				**Wages (’1000)**			
					Non-SSS		**SSS**	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
147	3700	Lake Charles, Louisiana	313,302	2	52	51	47	58
148	19901	Seaford, Delaware	310,840	4	40	52	43	70
149	8800	Savannah, Georgia	310,596	4	43	46	45	77
150	26002	Duluth, Minnesota	309,629	1	51	53	48	60
151	6600	Rome, Georgia	309,088	3	39	43	46	70
152	11101	Montgomery, Alabama	307,620	3	42	49	50	59
153	1203	Asheville, North Carolina	306,253	4	39	47	48	56
154	33300	Tyler, Texas	303,603	2	45	51	46	54
155	35801	Boise City-Nampa, Idaho	301,689	1	47	49	51	67
156	17900	Binghamton, New York	301,336	4	46	51	45	57
157	28800	Fort Collins-Loveland, Colorado	295,135	1	49	56	48	75
158	13700	Elkhart-Goshen, Indiana	294,594	4	47	48	46	55
159	9900	Tallahassee, Florida	293,859	2	40	49	46	67
160	7200	Cape Coral-Fort Myers, Florida	291,237	3	41	47	45	69
161	700	Spartanburg, South Carolina	287,754	4	39	47	46	67
162	16100	State College, Pennsylvania	286,894	3	45	48	46	62
163	11500	Jackson, Michigan	283,514	4	51	52	52	64
164	9701	Columbus, Georgia	282,425	4	39	44	46	62
165	1100	Hickory-Morganton-Lenoir, North Carolina	280,491	5	36	49	43	65
166	37300	Chico, California	279,971	2	47	50	50	53
167	22800	Eau Claire, Wisconsin	276,277	2	45	48	45	65
168	30100	Fort Smith, Arkansas	274,570	2	39	43	40	58
169	6100	Gadsden, Alabama	273,744	3	43	44	44	53
170	16702	Morgantown, West Virginia	273,000	4	46	56	45	53
171	29204	Topeka, Kansas	271,593	3	47	51	47	77
172	25601	Carbondale, Illinois	267,247	3	48	53	47	71
173	3400	Houma-Bayou Cane-Thibodaux, Louisiana	263,213	3	53	52	50	52
174	30802	Lubbock, Texas	262,506	2	45	49	48	54
175	39100	Kennewick-Richland-Pasco, Washington	262,341	1	52	52	59	80
176	20200	Burlington-South Burlington, Vermont	259,455	3	44	58	48	69
177	20001	Bangor, Maine	257,785	1	40	50	42	69
178	14400	Terre Haute, Indiana	257,619	3	45	50	42	51
179	13400	Lima, Ohio	256,578	4	49	49	43	57
180	28101	Lincoln, Nebraska	256,077	3	45	51	46	59
181	24802	Springfield, Illinois	256,018	3	47	60	49	54
182	37604	Reno-Sparks, Nevada	254,659	1	49	50	56	71
183	33400	Longview, Texas	252,821	2	47	49	44	59
184	3901	Monroe, Louisiana	252,300	2	44	45	49	44
185	22601	Green Bay, Wisconsin	248,795	3	49	53	49	80
186	31900	Houston-Baytown-Sugar Land, Texas	247,657	2	55	68	52	74
187	13300	Findlay, Ohio	245,119	3	48	51	43	55
188	14600	Bloomington, Indiana	245,026	3	44	49	42	48
189	22001	Waterloo-Cedar Falls, Iowa	243,203	3	52	49	49	53
190	1500	Wilmington, North Carolina	243,038	2	41	50	41	68
191	29601	Columbia, Missouri	238,024	2	44	48	46	59
192	10801	Tuscaloosa, Alabama	237,861	2	42	51	42	55
193	29901	Joplin, Missouri	236,572	2	42	47	45	54
194	15600	Wheeling, Ohio	236,142	4	50	49	44	47
195	17000	Non-Metro Area, Kentucky	233,216	3	52	46	52	42
196	36000	Provo-Orem, Utah	232,606	1	53	56	51	94
197	22200	Cedar Rapids, Iowa	229,254	3	50	55	53	70
198	30300	Fayetteville-Springdale-Rogers, Arkansas	228,845	2	37	54	48	64
199	20302	Lebanon, New hampshire	228,031	2	42	52	45	81
200	18300	Ogdensburg-Massena, New York	227,533	2	45	48	43	78

TABLE SM.1: Complete List of Commuting Zones and Wages (2015 USD)

		Commuting Zone			Wages (’1000)			
					Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
201	32801	Waco, Texas	227,126	2	42	44	47	72
202	18900	Williamsport, Pennsylvania	226,655	2	42	48	43	53
203	32900	Killeen-Temple-Fort Hood, Texas	226,592	3	40	45	42	59
204	11201	Bluefield, West Virginia	226,003	3	46	44	46	47
205	31401	Odessa, Texas	225,236	1	52	66	50	67
206	36301	Idaho Falls, Idaho	224,471	1	46	50	56	63
207	7900	Gainesville, Florida	214,946	2	40	52	46	67
208	15700	Portsmouth, Ohio	214,527	3	46	47	44	49
209	6200	Florence, Alabama	211,471	2	43	45	40	54
210	33500	Texarkana, TX-Texarkana, Texas	208,688	2	43	44	40	43
211	15300	Parkersburg-Marietta, West Virginia	208,283	3	47	49	41	47
212	18201	Olean, New York	205,800	2	42	44	43	47
213	10302	Dothan, Alabama	200,541	2	37	47	45	54
214	38700	Longview-Kelso, Washington	199,420	2	54	51	47	71
215	30903	Amarillo, Texas	199,141	1	47	52	48	56
216	16801	Beckley, West Virginia	198,224	3	47	45	45	33
217	13900	Kokomo, Indiana	197,729	4	50	46	46	45
218	39000	Yakima, Washington	197,385	1	46	43	49	69
219	8503	Valdosta, Georgia	195,941	2	36	42	44	64
220	2300	Lynchburg, Virginia	194,178	3	41	47	46	62
221	17600	Charlottesville, Virginia	194,059	2	41	59	48	82
222	3600	Alexandria, Louisiana	193,378	3	42	50	45	43
223	36800	Medford, Oregon	191,311	2	48	44	47	89
224	22900	La Crosse, Wisconsin	191,191	2	44	50	47	51
225	1800	Goldsboro, North Carolina	187,693	3	34	39	38	53
226	5900	Clarksville, Tennessee	187,014	2	40	43	38	52
227	34001	Hot Springs, Arkansas	187,011	1	40	40	40	53
228	21701	Rochester, Minnesota	186,793	2	52	64	51	67
229	1600	Rocky Mount, North Carolina	186,273	4	37	40	42	63
230	22400	Sheboygan, Wisconsin	183,853	5	46	51	48	63
231	18700	Sunbury, Pennsylvania	183,510	4	41	46	42	55
232	15400	Zanesville, Ohio	181,947	3	46	45	42	50
233	28001	Sioux City, Iowa	181,825	2	46	45	51	62
234	21400	St. Cloud, Minnesota	181,686	2	47	54	50	61
235	4102	Pine Bluff, Arkansas	181,221	1	43	44	43	49
236	23400	Bloomington-Normal, Illinois	178,638	2	48	53	57	84
237	20902	Pittsfield, Massachusetts	178,455	4	45	54	46	73
238	7800	Ocala, Florida	177,191	3	39	42	46	57
239	25900	Jonesboro, Arkansas	176,912	2	35	43	38	48
240	25701	Cape Girardeau-Jackson, Missouri	176,465	2	39	45	40	51
241	35500	Gallup, Arizona	176,273	1	47	42	49	59
242	4901	Jackson, Tennessee	175,554	3	37	54	46	56
243	26801	Fargo, North Dakota	174,614	1	46	52	49	68
244	8000	Sumter, South Carolina	173,651	3	36	41	39	50
245	22100	Iowa City, Iowa	172,984	2	48	55	47	53
246	32501	Abilene, Texas	172,513	1	42	46	47	66
247	23200	Dubuque, Iowa	172,404	2	49	49	47	62
248	17300	Staunton-Waynesboro, Virginia	172,281	2	39	45	39	59
249	33601	Lawton, Oklahoma	171,507	2	41	46	43	53
250	28502	Pueblo, Colorado	170,542	1	49	47	46	55
251	13200	Owensboro, Kentucky	168,848	3	48	48	47	59
252	5000	Tupelo, Mississippi	168,416	2	36	43	44	55
253	38100	El Centro, California	168,315	1	47	45	48	59
254	200	Sevierville, Tennessee	167,545	3	37	40	43	43

TABLE SM.1: Complete List of Commuting Zones and Wages (2015 USD)

					Wages (’1000)			
		Commuting Zone			Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
255	10200	Albany, Georgia	167,397	2	40	46	43	64
256	23700	Galesburg, Illinois	164,704	2	50	49	50	63
257	15500	Weirton-Steubenville, Ohio	163,734	6	54	48	46	47
258	4800	Greenville, Mississippi	163,630	2	37	39	42	40
259	18400	Plattsburgh, New York	161,855	1	42	45	42	67
260	13000	Elizabethtown, Kentucky	161,402	3	41	45	45	58
261	6502	Cleveland, Tennessee	159,158	3	41	47	47	80
262	29403	Bartlesville, Oklahoma	158,657	2	44	45	43	48
263	36902	Roseburg, Oregon	157,795	1	49	45	46	42
264	25000	Quincy, Illinois	156,609	2	43	43	41	57
265	10600	Birmingham-Hoover, Alabama	155,916	2	44	48	43	55
266	9400	Gainesville, Georgia	155,596	3	39	46	42	77
267	17800	Oneonta, New York	155,243	2	41	46	39	65
268	17501	Cumberland, Maryland	154,512	2	43	47	39	52
269	36600	Redding, California	154,501	1	49	50	48	47
270	29503	St. Joseph, Missouri	152,839	2	43	47	44	73
271	26503	Sioux Falls, South Dakota	152,765	2	46	50	48	62
272	5300	Memphis, Arkansas	151,102	2	38	39	43	48
273	23600	Burlington, Iowa	149,683	2	48	46	45	76
274	22300	Ottumwa, Iowa	148,953	1	44	49	43	59
275	25200	Madisonville, Kentucky	148,846	2	48	47	47	48
276	33200	Dallas-Plano-Irving, Texas	148,430	1	44	52	41	64
277	32201	Lufkin, Texas	148,359	1	43	46	44	60
278	10400	Meridian, Mississippi	148,134	2	37	42	46	39
279	35401	Prescott, Arizona	147,177	1	46	54	43	59
280	2200	Richmond, Virginia	146,161	1	36	41	40	66
281	14300	Columbus, Indiana	144,887	3	48	51	50	48
282	31101	Victoria, Texas	144,833	1	46	51	48	56
283	33902	Sherman-Denison, Texas	144,616	2	43	47	44	62
284	29203	Manhattan, Kansas	144,535	1	41	47	47	49
285	21301	Mankato-North Mankato, Minnesota	143,683	2	44	48	45	51
286	34802	Santa Fe, New Mexico	141,856	1	41	47	60	84
287	4502	Non-Metro Area, Kentucky	139,161	3	48	43	46	28
288	4702	Oxford, Mississippi	139,088	2	38	40	42	53
289	32601	Wichita Falls, Texas	137,930	2	42	47	48	47
290	9500	Talladega-Sylacauga, Alabama	137,672	2	36	43	40	53
291	2600	Roanoke Rapids, North Carolina	137,406	2	36	39	39	54
292	25500	Centralia, Illinois	137,342	2	47	51	50	74
293	15800	Athens, Ohio	137,183	3	46	44	43	61
294	1002	Hickory-Morganton-Lenoir, North Carolina	137,001	3	35	41	38	51
295	24200	Kankakee-Bradley, Illinois	135,902	3	48	53	49	55
296	9301	Athens-Clarke County, Georgia	134,955	4	39	48	40	59
297	5401	Bowling Green, Kentucky	134,729	2	38	50	41	58
298	31800	College Station-Bryan, Texas	134,134	2	45	50	43	59
299	27601	Rapid City, South Dakota	132,228	1	43	46	50	46
300	35201	Grand Junction, Colorado	132,224	1	49	52	50	59
301	30200	Muskogee, Oklahoma	131,854	2	38	42	41	42
302	17200	Harrisonburg, Virginia	131,579	2	40	52	42	76
303	11401	Marquette, Michigan	130,848	1	47	47	48	64
304	25401	Paducah, Kentucky	129,845	2	45	48	43	63
305	2900	Hattiesburg, Mississippi	129,476	2	40	43	48	52
306	36501	Klamath Falls, Oregon	129,120	1	46	49	46	53
307	34308	Billings, Montana	127,186	1	48	52	50	64
308	4401	London, Kentucky	125,369	3	41	41	43	40

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					Wages (’1000)			
		Commuting Zone			**Non-SSS**		**SSS**	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
309	19902	Baltimore-Towson, Maryland	121,573	2	42	54	46	87
310	25800	Blytheville, Arkansas	120,828	2	38	44	38	48
311	36700	Eureka-Arcata-Fortuna, California	120,383	1	48	47	47	44
312	5100	Corinth, Mississippi	120,300	2	35	42	45	46
313	5500	Columbia, Tennessee	120,269	2	37	42	36	59
314	21600	Brainerd, Minnesota	119,245	1	45	53	44	50
315	11301	Washington-Arlington-Alexandria, Virginia	118,674	3	47	62	56	84
316	11800	Mount Pleasant, Michigan	118,380	3	55	45	46	56
317	5800	Nashville-Davidson–Murfreesboro, Tennessee	117,836	2	42	44	46	72
318	27402	Fort Dodge, Iowa	117,291	1	45	46	40	47
319	21900	Marshalltown, Iowa	116,916	2	47	51	47	65
320	10000	Panama City-Lynn Haven, Florida	116,059	2	38	47	40	51
321	23000	Platteville, Wisconsin	115,716	2	45	46	45	59
322	13800	Warsaw, Indiana	115,530	3	45	48	47	41
323	30502	Enid, Oklahoma	115,475	1	46	49	43	57
324	25300	Mayfield, Kentucky	114,762	2	41	47	42	51
325	12800	Cincinnati-Middletown, Indiana	114,409	2	46	49	47	44
326	24600	Farmington, Missouri	114,356	1	42	46	42	53
327	9800	Auburn-Opelika, Alabama	113,708	2	38	49	43	61
328	26704	Grand Forks, North Dakota	113,674	1	43	49	47	79
329	18500	Gloversville, New York	113,626	2	39	49	41	51
330	2800	Laurel, Mississippi	113,389	2	38	42	46	51
331	35300	Farmington, New Mexico	113,125	1	47	52	47	56
332	33700	Ardmore, Oklahoma	111,988	1	41	47	45	55
333	12600	Richmond, Indiana	111,190	4	45	45	45	46
334	31503	Laredo, Texas	111,054	1	36	41	39	39
335	26901	Fergus Falls, Minnesota	109,926	1	44	55	47	50
336	9200	Atlanta-Sandy Springs-Marietta, Georgia	108,714	3	44	53	49	67
337	11402	Marinette, Wisconsin	108,663	1	45	49	44	66
338	30000	Russellville, Arkansas	108,262	1	39	40	43	50
339	12301	Traverse City, Michigan	107,257	2	44	49	50	66
340	4602	Somerset, Kentucky	107,039	2	34	39	33	50
341	39302	Bellingham, Washington	106,701	2	53	56	52	59
342	24500	Fort Leonard Wood, Missouri	104,942	1	40	42	40	45
343	2100	Washington, North Carolina	104,329	1	38	43	40	54
344	26201	Bismarck, North Dakota	104,270	1	48	64	46	70
345	5700	Tullahoma, Tennessee	102,720	2	36	43	48	55
346	36200	Logan, Utah	102,551	1	47	56	41	78
347	34504	Missoula, Montana	102,184	1	47	49	42	51
348	23301	Charleston-Mattoon, Illinois	101,960	2	45	46	48	65
349	7700	Lake City, Florida	101,908	1	40	44	43	44
350	23302	Effingham, Illinois	100,530	1	46	46	49	51
351	20700	Keene, New hampshire	99,049	2	43	54	46	64
352	3101	McComb, Mississippi	99,032	1	40	43	47	47
353	30701	Roswell, New Mexico	98,958	1	44	52	41	56
354	12001	Big Rapids, Michigan	98,711	1	44	46	45	59
355	8601	Waycross, Georgia	98,151	1	37	45	39	83
356	13502	Defiance, Ohio	97,658	3	48	49	51	51
357	9001	Non-Metro Area, Georgia	96,283	1	36	43	43	49
358	34002	Non-Metro Area, Oklahoma	96,194	1	39	42	38	49
359	34203	Great Falls, Montana	95,925	1	44	47	46	65
360	10502	Starkville, Mississippi	95,870	2	37	43	42	71
361	4103	El Dorado, Arkansas	95,708	1	41	50	43	48
362	12502	Wilmington, Ohio	95,547	3	46	51	40	58

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					Wages (’1000)			
		Commuting Zone			**Non-SSS**		**SSS**	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
363	21302	Faribault-Northfield, Minnesota	94,863	3	46	51	46	67
364	11203	Non-Metro Area, Virginia	94,382	3	45	47	43	43
365	4402	Richmond, Kentucky	93,816	2	38	48	38	49
366	35701	Twin Falls, Idaho	93,736	1	40	40	42	40
367	402	Martinsville, Virginia	93,450	3	38	46	39	57
368	32301	San Angelo, Texas	93,392	1	40	55	44	84
369	35600	Hilo, Hawaii	92,053	1	43	50	45	60
370	30801	Hobbs, New Mexico	92,023	1	47	54	42	64
371	10501	Columbus, Mississippi	91,997	2	37	44	42	62
372	20003	Non-Metro Area, Maine	91,344	1	38	46	42	41
373	20301	Berlin, New hampshire	90,708	1	41	50	46	81
374	29800	Branson, Missouri	89,435	1	36	42	40	60
375	8701	Hinesville-Fort Stewart, Georgia	89,419	2	39	45	42	49
376	24801	Jacksonville, Illinois	89,165	1	44	47	45	57
377	27101	Willmar, Minnesota	88,869	1	44	52	43	49
378	3203	Vicksburg, Mississippi	88,777	2	42	48	43	53
379	26701	Bemidji, Minnesota	88,712	1	43	50	43	55
380	32202	Nacogdoches, Texas	87,357	1	43	48	46	73
381	4902	Dyersburg, Tennessee	86,991	2	37	48	41	40
382	8702	Statesboro, Georgia	86,982	1	37	44	44	57
383	39203	Bend, Oregon	86,832	1	49	60	48	68
384	5402	Glasgow, Kentucky	86,213	2	35	43	41	42
385	34603	Casper, Wyoming	85,925	1	54	60	52	58
386	11202	Non-Metro Area, West Virginia	85,892	3	52	46	46	33
387	4701	Greenwood, Mississippi	85,782	2	34	40	40	63
388	12401	Alpena, Michigan	84,671	1	47	45	40	56
389	21801	Mason City, Iowa	84,376	2	46	46	44	52
390	4302	Searcy, Arkansas	83,703	1	36	55	42	64
391	27702	Cheyenne, Wyoming	83,588	1	52	58	51	55
392	29005	Hutchinson, Kansas	83,523	1	45	45	42	53
393	38401	Lewiston, Idaho	81,788	1	48	49	46	63
394	601	North Wilkesboro, North Carolina	80,982	2	32	40	36	62
395	21802	Non-Metro Area, Iowa	80,353	1	46	47	44	54
396	21101	Non-Metro Area, Wisconsin	80,336	1	43	49	46	53
397	32802	Corsicana, Texas	79,971	1	41	43	42	59
398	34503	Kalispell, Montana	79,697	1	47	50	42	91
399	23802	Clinton, Iowa	79,625	2	50	50	48	64
400	17502	Winchester, Virginia	79,199	2	41	55	45	89
401	26304	Minot, North Dakota	79,097	1	47	63	51	72
402	6302	Cookeville, Tennessee	79,021	2	35	40	45	62
403	11102	Troy, Alabama	79,010	1	36	43	44	54
404	25102	West Plains, Missouri	77,975	1	33	39	43	62
405	3202	Natchez, Mississippi	77,785	1	40	45	44	46
406	6402	Crossville, Tennessee	77,215	2	37	43	46	58
407	11002	Non-Metro Area, Alabama	76,975	1	41	49	48	62
408	29504	Sedalia, Missouri	76,855	1	40	43	38	59
409	21702	Austin, Minnesota	76,719	2	46	50	46	65
410	4601	Campbellsville, Kentucky	75,980	2	33	38	32	45
411	36404	Rock Springs, Wyoming	74,338	1	56	60	54	68
412	4003	Ruston, Louisiana	74,337	1	41	47	40	57
413	9302	Toccoa, Georgia	74,289	3	34	47	39	73
414	30401	Stillwater, Oklahoma	74,008	2	43	47	42	56
415	12903	Danville, Kentucky	73,983	3	40	48	43	53
416	29501	Kansas City, Kansas	73,206	3	44	49	44	65

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					Wages (’1000)			
		Commuting Zone			Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
417	27903	Grand Island, Nebraska	72,709	1	43	50	48	41
418	8602	Brunswick, Georgia	71,728	2	42	52	43	60
419	12402	Non-Metro Area, Michigan	71,618	1	46	44	41	53
420	34703	Kahului-Wailuku, Hawaii	70,991	2	43	48	45	66
421	29302	Wichita, Kansas	70,908	1	45	50	41	61
422	6301	McMinnville, Tennessee	70,537	2	35	40	45	66
423	27701	Scottsbluff, Nebraska	70,497	1	42	46	43	50
424	33802	Oklahoma City, Oklahoma	70,395	1	43	50	46	62
425	27202	Worthington, Minnesota	70,262	1	42	45	40	49
426	27301	Spencer, Iowa	69,817	1	46	45	49	51
427	10802	Tuscaloosa, Alabama	69,815	1	39	46	45	43
428	1301	Bennettsville, South Carolina	69,795	2	35	44	41	58
429	38402	Pullman, Washington	68,852	1	47	50	45	64
430	30901	Clovis, New Mexico	68,752	1	41	45	42	52
431	26902	Non-Metro Area, Minnesota	68,494	1	43	55	41	46
432	39303	Port Angeles, Washington	67,613	1	53	47	47	54
433	38502	Wenatchee, Washington	67,205	1	46	47	46	51
434	25702	Poplar Bluff, Missouri	66,856	1	35	40	43	46
435	8201	Non-Metro Area, South Carolina	66,845	1	36	38	40	37
436	30904	Borger, Texas	65,853	1	46	49	42	42
437	301	Middlesborough, Kentucky	65,812	2	42	43	47	55
438	33901	Ada, Oklahoma	65,725	1	40	47	43	55
439	21201	Hutchinson, Minnesota	65,699	2	46	52	48	54
440	38602	Non-Metro Area, Washington	65,453	1	46	47	45	56
441	9002	Milledgeville, Georgia	64,815	2	36	47	44	54
442	9003	Dublin, Georgia	64,492	1	36	45	44	57
443	34402	Bozeman, Montana	64,398	1	45	54	48	78
444	16701	Non-Metro Area, West Virginia	63,967	1	40	43	40	47
445	28702	Edwards, Colorado	63,850	1	49	48	51	64
446	33801	Non-Metro Area, Oklahoma	63,835	1	42	48	50	41
447	12302	Non-Metro Area, Michigan	63,548	2	45	47	47	55
448	16802	Non-Metro Area, West Virginia	62,599	1	41	44	42	38
449	38501	Moses Lake, Washington	61,789	1	46	46	45	61
450	14801	Non-Metro Area, Illinois	61,471	1	44	48	50	45
451	27201	Non-Metro Area, Iowa	60,681	1	45	45	52	51
452	9702	Americus, Georgia	60,330	1	34	43	42	70
453	34404	Butte-Silver Bow, Montana	60,268	1	45	50	48	53
454	27802	Columbus, Nebraska	60,203	1	45	43	48	50
455	27401	Storm Lake, Iowa	60,038	1	44	46	49	50
456	602	Non-Metro Area, Virginia	59,960	2	35	42	42	56
457	1001	Boone, North Carolina	59,820	3	33	39	37	48
458	14802	Vincennes, Indiana	59,645	2	44	46	43	51
459	26101	Moberly, Missouri	59,315	1	42	42	43	52
460	22602	Non-Metro Area, Wisconsin	59,279	1	43	50	43	60
461	10301	Non-Metro Area, Alabama	59,140	1	36	41	44	54
462	29104	Salina, Kansas	59,021	1	42	44	45	56
463	25103	Harrison, Arkansas	58,873	1	35	42	46	40
464	26605	Aberdeen, South Dakota	58,676	1	38	46	43	53
465	10102	Thomasville, Georgia	57,943	2	34	40	43	57
466	27302	Fairmont, Minnesota	57,737	1	44	45	46	50
467	30908	Plainview, Texas	57,149	1	42	43	45	53
468	21004	Non-Metro Area, Wisconsin	56,795	1	42	47	45	63
469	38902	Non-Metro Area, Oregon	56,428	1	51	46	43	58
470	13103	Louisville, Kentucky	56,258	2	38	44	43	56

Table SM.1: Complete List of Commuting Zones and Wages (2015 USD)

		Commuting Zone			Wages (’1000)			
					Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
471	28201	Non-Metro Area, Iowa	55,961	1	43	48	42	63
472	27102	Marshall, Minnesota	55,807	1	42	48	39	46
473	30602	Alamogordo, New Mexico	55,662	1	39	46	41	48
474	32401	Big Spring, Texas	55,624	1	52	49	48	36
475	38802	City of The Dalles, Oregon	55,561	1	51	49	48	57
476	25105	Batesville, Arkansas	55,522	1	36	38	42	76
477	27801	Norfolk, Nebraska	55,087	1	45	43	54	46
478	33602	Altus, Oklahoma	54,614	1	42	48	50	41
479	29303	Winfield, Kansas	54,522	1	42	48	33	60
480	27504	Non-Metro Area, Iowa	54,005	1	44	46	47	49
481	29004	Great Bend, Kansas	53,889	1	44	51	43	46
482	32701	Brownwood, Texas	53,814	1	39	45	41	48
483	34403	Helena, Montana	53,335	1	45	50	48	53
484	1702	Henderson, North Carolina	52,980	3	33	40	36	63
485	26102	Marshall, Missouri	52,783	1	40	43	39	65
486	12702	Maysville, Kentucky	52,366	2	37	44	41	50
487	29602	Non-Metro Area, Missouri	52,363	1	37	42	41	53
488	35802	Ontario, Oregon	51,524	1	43	45	44	60
489	29401	Kansas City, Kansas	51,065	1	44	49	38	60
490	28608	Kearney, Nebraska	50,453	1	43	52	47	54
491	29902	Non-Metro Area, Missouri	50,375	1	39	43	37	54
492	30403	Tulsa, Oklahoma	50,294	1	40	43	42	47
493	27005	Yankton, South Dakota	49,843	1	42	47	45	64
494	11303	Non-Metro Area, Virginia	49,814	2	38	49	48	89
495	12002	Non-Metro Area, Michigan	49,384	2	44	47	46	66
496	4501	Non-Metro Area, Kentucky	49,268	1	46	44	41	39
497	28609	Lexington, Nebraska	48,638	1	45	51	48	54
498	5201	Non-Metro Area, Mississippi	48,633	1	35	43	41	50
499	4301	Non-Metro Area, Arkansas	48,367	1	40	50	46	57
500	21002	Houghton, Michigan	48,319	1	43	50	39	78
501	35902	Price, Utah	48,250	1	51	57	49	68
502	30604	Silver City, New Mexico	47,838	1	49	38	42	79
503	35901	St. George, Utah	47,792	1	46	59	43	54
504	29402	Emporia, Kansas	47,787	1	45	49	41	60
505	25101	Mountain Home, Arkansas	46,704	1	35	41	46	42
506	21001	Non-Metro Area, Wisconsin	46,393	1	42	45	45	45
507	13102	Madison, Indiana	45,942	3	46	53	47	60
508	19903	Non-Metro Area, Virginia	45,893	3	38	49	48	89
509	11403	Sault Ste. Marie, Michigan	45,866	1	45	44	49	47
510	18202	St. Marys, Pennsylvania	45,012	1	43	45	43	55
511	21102	Non-Metro Area, Wisconsin	44,691	1	44	50	46	56
512	26803	Jamestown, North Dakota	44,587	1	42	50	49	63
513	28102	Non-Metro Area, Nebraska	44,087	1	42	48	42	64
514	27901	Hastings, Nebraska	43,620	1	43	52	48	55
515	32702	Stephenville, Texas	43,474	1	41	47	41	78
516	1202	Non-Metro Area, North Carolina	43,311	1	36	46	38	54
517	34304	Sheridan, Wyoming	42,844	1	51	60	47	64
518	3001	Non-Metro Area, Mississippi	42,835	1	34	46	40	62
519	3102	Brookhaven, Mississippi	42,692	2	39	46	46	51
520	31303	Kerrville, Texas	42,312	1	40	53	43	79
521	16703	Non-Metro Area, West Virginia	42,240	2	39	42	40	50
522	10101	Bainbridge, Georgia	41,590	1	34	40	43	57
523	25602	Harrisburg, Illinois	41,421	2	43	52	42	52
524	3002	Yazoo City, Mississippi	41,280	1	42	48	43	55

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		Commuting Zone			Wages (’1000)			
					Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
525	26107	Kirksville, Missouri	40,772	1	40	43	39	51
526	34801	Las Vegas, New Mexico	40,623	1	39	46	42	87
527	1204	Non-Metro Area, North Carolina	40,580	1	35	45	38	62
528	27503	Non-Metro Area, Iowa	40,534	1	44	48	42	63
529	26702	Non-Metro Area, North Dakota	40,078	1	42	49	48	79
530	39201	La Grande, Oregon	40,055	1	46	45	51	57
531	31402	Pecos, Texas	39,812	1	46	52	42	52
532	32305	Del Rio, Texas	39,784	1	34	47	35	34
533	21202	Non-Metro Area, Minnesota	39,742	1	45	51	44	48
534	31302	Beeville, Texas	39,623	1	44	50	43	70
535	28301	Sterling, Colorado	39,328	1	42	51	47	84
536	25104	Non-Metro Area, Arkansas	39,288	1	36	38	42	76
537	35702	Burley, Idaho	39,145	1	40	40	42	40
538	29006	Hays, Kansas	39,131	1	42	44	42	70
539	34702	Kapaa, Hawaii	39,082	2	43	48	45	66
540	34303	Riverton, Wyoming	38,992	1	56	60	54	57
541	27502	Non-Metro Area, Iowa	38,376	1	43	48	42	51
542	4903	Non-Metro Area, Tennessee	38,358	1	36	41	46	54
543	28306	North Platte, Nebraska	38,031	1	46	51	48	54
544	8502	Cordele, Georgia	37,997	1	35	43	42	68
545	24702	Mexico, Missouri	37,995	1	41	43	44	60
546	34805	Non-Metro Area, Colorado	37,914	1	42	47	47	44
547	26501	Brookings, South Dakota	37,703	1	40	47	44	62
548	31102	Non-Metro Area, Texas	37,655	1	44	49	45	56
549	29505	Maryville, Missouri	37,483	1	41	44	37	63
550	30902	Non-Metro Area, Texas	37,393	1	43	44	44	51
551	4001	Magnolia, Arkansas	36,857	1	41	47	42	49
552	34601	Gillette, Wyoming	36,781	1	53	61	49	61
553	26504	Watertown, South Dakota	36,329	1	40	47	44	62
554	21003	Non-Metro Area, Michigan	36,277	1	43	49	40	71
555	36901	Crescent City North, California	35,209	1	47	50	46	59
556	12902	Mount Sterling, Kentucky	35,188	2	37	44	41	50
557	20002	Non-Metro Area, Maine	34,963	1	38	46	35	41
558	22002	Non-Metro Area, Iowa	34,812	1	46	49	47	60
559	29003	Dodge City, Kansas	34,321	1	45	45	53	60
560	35002	Safford, Arizona	34,268	1	46	45	38	67
561	26106	Non-Metro Area, Iowa	34,023	1	43	48	42	51
562	26703	Non-Metro Area, Minnesota	33,756	1	42	51	40	66
563	34301	Non-Metro Area, Wyoming	33,601	1	53	61	47	65
564	31001	Garden City, Kansas	33,588	1	45	45	53	60
565	36402	Vernal, Utah	33,071	1	53	56	53	75
566	36401	Non-Metro Area, Colorado	32,792	1	49	51	50	71
567	32304	Uvalde, Texas	32,073	1	35	47	38	34
568	21502	Non-Metro Area, Minnesota	32,032	1	47	55	47	49
569	30501	Woodward, Oklahoma	31,483	1	45	49	39	47
570	32306	Eagle Pass, Texas	31,398	1	33	46	35	34
571	8402	Non-Metro Area, Georgia	31,090	1	37	49	44	71
572	28704	Laramie, Wyoming	30,925	1	54	59	52	56
573	37601	Elko, Nevada	30,710	1	48	58	50	58
574	1201	Non-Metro Area, North Carolina	30,644	1	35	45	38	60
575	35402	Non-Metro Area, Colorado	30,421	1	47	48	49	75
576	25402	Murray, Kentucky	30,031	3	46	48	43	64
577	26412	Williston, North Dakota	29,553	1	47	66	51	67
578	26410	Dickinson, North Dakota	29,462	1	47	66	51	67

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					Wages (’1000)			
		Commuting Zone			**Non-SSS**		**SSS**	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
579	3201	Non-Metro Area, Louisiana	29,291	1	41	51	42	46
580	27902	Non-Metro Area, Nebraska	29,038	1	42	48	42	64
581	31004	Liberal, Kansas	28,665	1	45	46	50	59
582	32602	Non-Metro Area, Texas	28,544	1	43	50	43	57
583	32403	Snyder, Texas	28,425	1	41	46	41	62
584	27006	Mitchell, South Dakota	28,076	1	40	45	39	63
585	31006	Guymon, Oklahoma	28,003	1	45	49	42	49
586	31202	Non-Metro Area, Texas	27,947	1	39	45	41	48
587	28002	Non-Metro Area, Nebraska	27,663	1	46	43	50	46
588	34201	Havre, Montana	27,313	1	44	47	46	65
589	31007	Dumas, Texas	27,093	1	46	49	42	42
590	26411	Non-Metro Area, Montana	27,054	1	46	61	48	71
591	4101	Non-Metro Area, Arkansas	26,538	1	39	43	41	54
592	37903	Bishop, California	26,472	1	47	60	40	62
593	26301	Non-Metro Area, North Dakota	26,225	1	42	50	49	68
594	26103	Non-Metro Area, Missouri	25,984	1	40	43	39	57
595	6501	Non-Metro Area, Georgia	25,858	1	40	43	48	73
596	29101	Non-Metro Area, Kansas	25,304	1	42	44	45	56
597	4004	Non-Metro Area, Louisiana	25,280	1	42	47	42	65
598	8501	Fitzgerald, Georgia	24,988	2	37	42	44	100
599	3902	Non-Metro Area, Louisiana	24,694	1	40	41	36	44
600	32604	Vernon, Texas	24,457	1	44	51	43	57
601	26602	Non-Metro Area, South Dakota	24,448	1	38	46	43	53
602	16902	Non-Metro Area, West Virginia	24,202	1	46	49	41	47
603	27703	Non-Metro Area, Wyoming	24,015	1	54	61	52	61
604	32302	Non-Metro Area, Texas	23,522	1	40	49	43	36
605	32402	Sweetwater, Texas	23,250	1	41	46	41	62
606	27008	Non-Metro Area, South Dakota	23,211	1	40	45	39	63
607	29201	Non-Metro Area, Kansas	23,166	1	44	49	44	65
608	31501	Non-Metro Area, Texas	23,033	1	33	46	35	34
609	34202	Non-Metro Area, Montana	22,918	1	44	47	46	65
610	28607	Non-Metro Area, Nebraska	22,808	1	46	51	48	54
611	26601	Non-Metro Area, South Dakota	22,271	1	42	51	43	57
612	27007	Huron, South Dakota	22,124	1	38	46	43	53
613	27704	Non-Metro Area, South Dakota	21,911	1	38	45	44	48
614	34602	Non-Metro Area, Wyoming	21,896	1	54	60	52	57
615	28503	Non-Metro Area, Colorado	21,337	1	42	47	47	43
616	29202	Non-Metro Area, Kansas	21,330	1	41	46	47	51
617	29001	Non-Metro Area, Kansas	20,869	1	44	51	43	46
618	29506	Non-Metro Area, Missouri	20,785	1	41	44	37	63
619	37603	Non-Metro Area, California	20,413	1	47	66	46	107
620	35904	Non-Metro Area, Utah	19,729	1	46	59	43	54
621	31005	Non-Metro Area, Texas	19,563	1	46	49	42	42
622	32503	Non-Metro Area, Texas	19,424	1	42	47	42	60
623	26802	Non-Metro Area, North Dakota	19,417	1	45	50	49	63
624	31502	Non-Metro Area, Texas	19,299	1	38	51	41	71
625	31403	Non-Metro Area, Texas	19,226	1	45	52	43	50
626	28604	Non-Metro Area, Kansas	19,199	1	42	44	42	70
627	27011	Pierre, South Dakota	18,743	1	36	45	44	63
628	28302	Non-Metro Area, Nebraska	18,729	1	45	50	47	61
629	27001	Non-Metro Area, Nebraska	17,943	1	42	46	43	49
630	34502	Non-Metro Area, Montana	17,752	1	47	50	42	91
631	26004	Non-Metro Area, Minnesota	17,571	1	47	52	47	53
632	31103	Non-Metro Area, Texas	16,949	1	46	52	48	55

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					Wages (’1000)			
		Commuting Zone			Non-SSS		SSS	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
633	26104	Non-Metro Area, Missouri	16,644	1	40	44	38	63
634	26001	Non-Metro Area, Minnesota	16,338	1	42	51	40	65
635	26303	Non-Metro Area, North Dakota	16,229	1	42	62	49	71
636	26305	Non-Metro Area, North Dakota	15,964	1	45	59	49	69
637	28305	Non-Metro Area, Nebraska	15,717	1	42	50	44	41
638	26409	Non-Metro Area, Montana	15,672	1	45	57	46	71
639	36403	Non-Metro Area, Idaho	15,626	1	47	47	48	54
640	26408	Non-Metro Area, Montana	15,617	1	44	55	46	73
641	34902	Non-Metro Area, New Mexico	15,286	1	43	38	51	79
642	34302	Non-Metro Area, Wyoming	15,206	1	53	61	47	61
643	34305	Non-Metro Area, Montana	14,945	1	45	55	46	73
644	26502	Non-Metro Area, South Dakota	14,463	1	40	47	44	62
645	31404	Non-Metro Area, Texas	14,408	1	46	52	42	52
646	29102	Non-Metro Area, Nebraska	14,308	1	42	50	45	60
647	26203	Non-Metro Area, North Dakota	14,170	1	45	63	48	72
648	29103	Non-Metro Area, Kansas	14,076	1	42	44	44	63
649	31002	Non-Metro Area, Kansas	14,052	1	45	45	53	60
650	34204	Non-Metro Area, Montana	13,731	1	45	55	46	73
651	26105	Non-Metro Area, Missouri	13,526	1	40	43	39	51
652	34307	Non-Metro Area, Montana	13,400	1	45	55	46	73
653	28603	Non-Metro Area, Kansas	13,353	1	42	44	42	70
654	27004	Non-Metro Area, South Dakota	13,283	1	36	45	44	63
655	28701	Non-Metro Area, Colorado	13,227	1	53	44	59	61
656	26406	Non-Metro Area, Montana	13,169	1	44	55	46	73
657	37602	Non-Metro Area, Nevada	12,857	1	48	58	50	58
658	26404	Non-Metro Area, South Dakota	12,559	1	43	60	49	60
659	33603	Non-Metro Area, Oklahoma	12,398	1	43	46	46	53
660	27002	Non-Metro Area, Nebraska	12,317	1	42	50	43	41
661	36303	Jackson, Wyoming	12,252	1	55	59	57	69
662	30906	Non-Metro Area, Texas	12,248	1	46	49	42	42
663	30905	Non-Metro Area, Texas	11,785	1	46	49	42	42
664	28504	Non-Metro Area, Colorado	11,688	1	42	51	47	84
665	34803	Non-Metro Area, New Mexico	11,667	1	39	44	42	53
666	35202	Non-Metro Area, Colorado	11,097	1	47	47	50	62
667	29007	Non-Metro Area, Kansas	11,001	1	42	44	42	70
668	27009	Non-Metro Area, South Dakota	10,904	1	38	45	41	63
669	36302	Non-Metro Area, Idaho	10,845	1	44	52	59	71
670	31003	Non-Metro Area, Kansas	10,668	1	45	45	53	60
671	32502	Non-Metro Area, Texas	9,897	1	44	50	43	47
672	28605	Non-Metro Area, Kansas	9,804	1	42	44	42	70
673	27605	Non-Metro Area, South Dakota	9,577	1	36	44	44	47
674	26604	Non-Metro Area, South Dakota	9,254	1	36	46	44	53
675	28304	Non-Metro Area, Nebraska	9,138	1	43	47	45	51
676	35803	Non-Metro Area, Idaho	8,951	1	42	45	41	65
677	20403	Non-Metro Area, Massachusetts	8,942	3	45	60	49	125
678	26603	Non-Metro Area, South Dakota	8,816	1	42	58	46	57
679	28601	Non-Metro Area, Kansas	8,614	1	42	44	42	70
680	30603	Non-Metro Area, New Mexico	8,454	1	42	38	53	79
681	36502	Non-Metro Area, Oregon	8,314	1	45	45	46	43
682	35903	Non-Metro Area, Utah	8,241	1	53	56	53	75
683	39205	Non-Metro Area, Oregon	8,210	1	46	48	51	52
684	34401	Non-Metro Area, Montana	8,186	1	45	54	48	78
685	26302	Non-Metro Area, North Dakota	8,165	1	42	50	49	63
686	27003	Non-Metro Area, Nebraska	8,061	1	42	46	43	50

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					Wages (’1000)			
		Commuting Zone			**Non-SSS**		**SSS**	
	CZ	Main Metro Area and State	1980 Pop	Decile	’80	’15	’80	’15
687	39301	Non-Metro Area, Washington	7,838	2	50	52	46	62
688	27602	Non-Metro Area, South Dakota	7,674	1	36	44	44	47
689	36503	Non-Metro Area, Oregon	7,532	1	45	45	46	43
690	28703	Non-Metro Area, Colorado	7,475	1	47	47	50	62
691	34501	Non-Metro Area, Idaho	7,289	1	48	48	46	64
692	39202	Non-Metro Area, Oregon	7,273	1	46	45	51	57
693	27010	Non-Metro Area, South Dakota	7,017	1	38	46	44	56
694	29008	Non-Metro Area, Kansas	6,970	1	45	45	53	60
695	30702	Non-Metro Area, New Mexico	6,950	1	39	46	42	85
696	28602	Non-Metro Area, Kansas	6,689	1	42	44	42	70
697	28606	Non-Metro Area, Kansas	6,539	1	44	47	45	65
698	32303	Non-Metro Area, Texas	6,409	1	40	49	44	36
699	27603	Non-Metro Area, South Dakota	6,231	1	36	44	44	47
700	37902	Non-Metro Area, Nevada	6,217	1	48	58	50	58
701	28501	Non-Metro Area, Colorado	5,419	1	42	47	47	43
702	26407	Non-Metro Area, Montana	5,414	1	44	55	46	73
703	26403	Non-Metro Area, North Dakota	5,386	1	47	66	51	67
704	20402	Non-Metro Area, Massachusetts	5,087	3	45	60	49	125
705	32603	Non-Metro Area, Texas	4,919	1	44	51	43	57
706	34804	Non-Metro Area, New Mexico	4,725	1	39	44	42	53
707	28402	Non-Metro Area, Colorado	4,663	1	42	51	47	84
708	34309	Non-Metro Area, Montana	4,513	1	45	54	47	76
709	26202	Non-Metro Area, North Dakota	4,274	1	48	66	46	67
710	26003	Non-Metro Area, Minnesota	4,092	1	47	52	47	53
711	26204	Non-Metro Area, North Dakota	3,833	1	48	63	46	72
712	26402	Non-Metro Area, Montana	3,763	1	45	55	46	73
713	26804	Non-Metro Area, North Dakota	3,714	1	42	50	49	63
714	31304	Non-Metro Area, Texas	3,683	1	40	49	44	36
715	27012	Non-Metro Area, South Dakota	3,674	1	36	44	44	47
716	39204	Non-Metro Area, Oregon	3,570	1	46	48	51	52
717	26401	Non-Metro Area, South Dakota	3,499	1	44	50	48	58
718	30605	Non-Metro Area, Texas	3,315	1	46	52	42	52
719	34604	Non-Metro Area, Wyoming	2,924	1	54	61	52	61
720	26405	Non-Metro Area, Montana	2,835	1	44	55	46	73
721	28303	Non-Metro Area, Nebraska	2,802	1	42	46	43	50
722	29002	Non-Metro Area, Kansas	2,554	1	44	51	43	46
723	30907	Non-Metro Area, Texas	1,950	1	41	42	46	56
724	35905	Non-Metro Area, Utah	1,911	1	46	59	43	54
725	34306	Non-Metro Area, Montana	1,656	1	45	55	46	73
726	27604	Non-Metro Area, South Dakota	1,463	1	36	44	44	47