Urban-Biased Growth: A Macroeconomic Analysis*

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Abstract

Since 1980, US wage growth has been concentrated in high-density locations, nearly doubling the wage-density elasticity across cities. We show that this urban-biased growth originates entirely at large, IT-intensive firms in the Business Services sector. We propose a simple explanation centered on the dramatic decline in IT prices over this period. First, a complementarity between IT capital and firm scale makes large firms benefit most from cheaper IT capital. Second, because large Business Services firms are concentrated in dense cities, falling IT prices generate urban-biased growth. Disciplining this mechanism with firm-level data, we find that the observed decline in IT prices accounts for approximately 75% of the increase in the wage-density gradient.

Keywords: Urban Growth, High-skill Services, Technological Change
JEL Codes: J31, O33, R11, R12

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Introduction

Since 1980, wage growth in the United States has been concentrated in large, densely populated cities. Over this period, the average wage gap between high-density cities such as New York or Chicago and the least dense parts of the country has increased from 32% in 1980 to 71% in 2015 (see Figure 1). This marks a sharp break from the postwar decades, when economic development occurred more evenly across space.

Urban-biased growth lies at the heart of many economic and societal challenges facing the United States. In cities like New York and San Francisco, rising wages have driven up housing costs and rents, fueling a severe affordability crisis for lower-income households (Gyourko, Mayer, and Sinai, 2013). At the same time, the geographic concentration of wage growth has deepened regional disparities and increased political polarization (Scala and Johnson, 2017), underscoring the need to understand the forces behind this transformation.

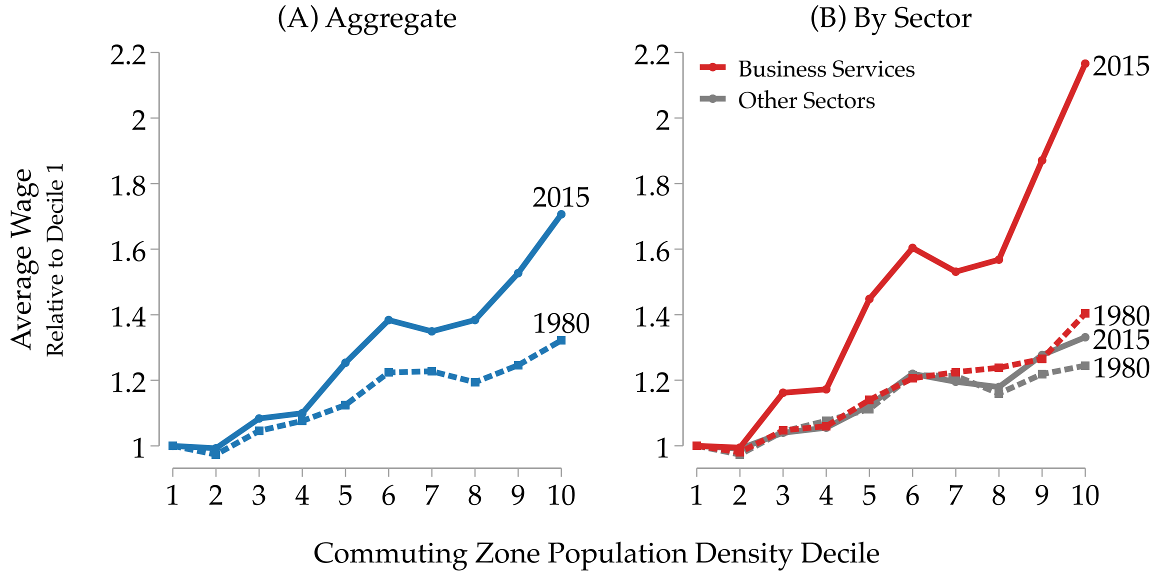
This paper shows that urban-biased wage growth originates entirely in the Business Services sector and is driven by falling information technology (IT) prices. Large, IT-intensive firms in this sector account for almost all the spatial divergence in wage growth since 1980. We develop a spatial growth model in which firms in high-density, high-productivity locations operate on a larger scale. A complementarity between IT capital and firm scale makes these firms more capital-intensive, amplifying the wage effects of declining IT prices in dense cities. Calibrating the model with firm-level data on capital–labor ratios, sales, and location choices, we find that this mechanism explains roughly 75 percent of the observed rise in the wage-density gradient.

We begin by showing that urban-biased wage growth is concentrated in Business Services.[1] The left panel of Figure 1 plots average wages against commuting zone population density, while the right panel shows this relationship separately for Business Services and all other sectors. Between 1980 and 2015, the wage gap between the highest- and lowest-density commuting zones in Business Services widened from 40 to 120 percent, while the wage-density gradient in all other sectors remained flat. This pattern implies that the aggregate increase in the wage-density gradient visible in the left panel is fully accounted for by Business Services.

These patterns rule out broad-based labor supply explanations of urban-biased growth that center on specific educational or occupational groups. For instance, if the phenomenon were driven by the sorting of college-educated workers into dense cities, one would expect all sectors to exhibit urban-biased growth, in proportion to their

[1] Business Services is a commonly used term that refers to the following group of 2-digit NAICS industries: Information (51), Finance and Insurance (52), Real Estate and Rental and Leasing (53), Professional, Scientific, and Technical Services (54), Management of Companies and Enterprises (55), and Administrative and Support and Waste Management and Remediation Services (56).

FIGURE 1: THE US WAGE-DENSITY GRADIENT IN 1980 AND 2015



Notes: This figure shows average wages across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density. Each decile accounts for one-tenth of the US population in 1980. The average commuting zone in decile 1 has a population density of 10 $people/mi^2$ and in decile 10 of 2300 $people/mi^2$. The underlying data come from the US Census Bureau's Longitudinal Business Database. We compute average wages as average payroll per worker by aggregating establishment payroll numbers and employment counts across all establishments in a commuting zone and sector.

college employment share. Instead, we show that this bias is confined to Business Services—and it appears for all workers in that sector, regardless of education or occupation.

A second set of empirical findings points to a labor-demand-driven mechanism linked to the rise of information technology, which has been the central driver of skill-biased wage growth in the US economy (Krusell, Ohanian, Ríos-Rull, and Violante, 2000). Within Business Services, urban-biased wage growth is concentrated in large establishments. These large establishments are disproportionately located in dense cities and use much more IT capital per worker than smaller establishments. This pattern suggests that an interaction between firm size, IT intensity, and local density plays a central role in driving spatial wage divergence.

In a general spatial model of firm production, we characterize the conditions under which declining capital prices generate urban-biased wage growth consistent with our empirical facts. In each location and sector, firms have to pay an entry cost to produce with a technology that uses freely traded capital and local labor. In this setting, a fall in capital prices leads to density-biased wage growth if three conditions are met: (i) entry costs depend on local inputs such as labor or land; (ii) capital and firm scale are complementary, so that larger firms operate with higher capital intensity; and (iii) labor productivity is positively correlated with population density across locations.

Together, these conditions link firm scale, capital intensity, and population density in equilibrium, making firms in dense locations larger and more exposed to capital price changes, consistent with the data. The mechanism operates as follows. In high-density locations, higher local productivity lowers marginal costs of production, spurring firm entry and bidding up local factor prices. These higher factor prices, in turn, raise entry costs. As a result, not all marginal cost advantages are competed away in equilibrium—otherwise, no firm would be willing to pay the elevated entry costs. The remaining marginal cost advantage allows firms in dense areas to operate on a larger scale, which raises their capital intensity via the capital–scale complementarity. As capital prices fall, the most capital-intensive experience the largest cost savings, resulting in the greatest wage gains in the dense locations where they operate.

To quantify the mechanism, we model the capital-scale complementarity as a non-homotheticity in production, using a non-homothetic CES aggregator as production technology (as in Lashkari, Bauer, and Boussard, 2024). When the non-homotheticity parameter is negative, larger firms choose higher capital-labor ratios; when it is zero, production is homothetic and capital intensity is invariant to firm size. This functional form serves as a reduced-form representation of a richer model in which firms choose from a menu of technologies, with more capital-intensive options requiring higher fixed costs, generating an equilibrium relationship between firm size and capital intensity (see Trottner, 2022).

Using this structure, we quantify the three core forces shaping the spatial wage response to falling IT prices using firm-level microdata, separately for each sector. First, we calibrate the share of local factors in entry costs to match the positive correlation between establishment size and commuting zone density. Second, we estimate the non-homotheticity parameter in production by matching the observed relationship between IT capital intensity and firm sales within location-sector cells. Third, we recover regional productivity and amenity terms as residuals that match wages and employment in 700 commuting zones in the US from 1980 to 2015, finding that productivity and population density are correlated. Each of these relationships is substantially stronger in Business Services, helping explain why urban-biased wage growth is concentrated in that sector.

We evaluate the *quantitative* contribution of the observed decline in IT capital prices to urban-biased growth using a general equilibrium counterfactual. In our main counterfactual, we feed the observed decline in IT capital prices into the model while holding productivity and amenity values fixed at their 1980 levels. The resulting wage changes account for about 75 percent of the observed increase in the wage-density gradient between 1980 and 2015. Consistent with our empirical facts, the wage growth response is concentrated among large Business Services firms.

When we eliminate the capital-scale complementarity by setting the non-homotheticity parameter to zero and recalibrating all residuals to match the same data, the model produces little urban-biased wage growth in response to falling IT prices. This confirms that the capital-scale complementarity is central to why declining IT prices explain so much of the spatial divergence in wage growth.

Our findings reinterpret the decline in IT prices as a form of technical change that is both skill-biased and urban-biased. They imply that the rise of the knowledge economy has systematically favored large firms in dense cities—not just high-skill workers—and helps explain the growing divergence in regional economic outcomes.

Literature Review. This paper is the first to document the doubling of the US wage-density gradient since 1980. Previous work has studied wage convergence and divergence (Berry and Glaeser, 2005; Moretti, 2012; Ganong and Shoag, 2017; Giannone, 2022), the unbalanced spatial growth of the college wage premium (Baum-Snow and Pavan, 2013; Eckert, 2019; Rubinton, 2025; Diamond, 2016), and patterns of within-city inequality (Davis and Dingel, 2020; Eeckhout, Hedtrich, and Pinheiro, 2021; Couture and Handbury, 2020; Almagro and Domínguez-Iino, 2025; Fogli, Guerrieri, Ponder, and Prato, 2023).

We also contribute by identifying large Business Services firms as the drivers of this shift and by showing how their production technologies transmit falling IT capital prices into spatial wage divergence. Although prior work has linked information technology to *skill*-biased wage growth (Krusell et al., 2000; Krueger, 1993; Lashkari et al., 2024), this article emphasizes its *spatial* consequences. Our analysis complements research on the impact of information technology across regions (Kleinman, Liu, and Redding, 2023; Rubinton, 2025; Jiang, 2023; Baum-Snow and Pavan, 2013) and a more general literature on the adoption of technology in space (Desmet and Rossi-Hansberg, 2014; Desmet, Nagy, and Rossi-Hansberg, 2018; Martellini, 2022; Bilal and Rossi-Hansberg, 2023; Nagy, 2023; Ganapati, 2025).

On the theoretical side, our paper is the first to show how the composition of entry costs and capital-scale complementarities interact to shape cross-sectional patterns of firm size and capital intensity. This contributes to a growing literature on the cross-sectional implications of firm entry (Klenow and Li, 2025) and to an emerging literature using non-homothetic CES production functions (Sato, 1977; Lashkari et al., 2024; Trottner, 2022), to which we contribute by embedding this technology in a quantitative spatial model (Allen and Arkolakis, 2014; Redding, 2016; Redding and Rossi-Hansberg, 2017).

1. Urban-Biased Growth in the Data

We begin by documenting the rise of urban-biased wage growth since 1980. This growth is concentrated at large Business Services establishments in dense cities. It holds across education groups within that sector but is absent for all groups outside it—indicating that the divergence reflects sectoral rather than worker-specific trends. Finally, we show that Business Services firms are among the most IT-intensive in the US economy, pointing to falling IT prices as a potential driver of the spatial divergence in wage growth.

1.1 Main Data Sources

Our primary data source is the Longitudinal Business Database (LBD), which covers all private, non-farm establishments in the United States. The LBD is constructed from administrative tax records and reports annual payroll and total employment for each establishment. An establishment refers to a single physical location where business is conducted, services are provided, or goods are produced.

We use data from 1980 to 2015, assigning each establishment to one of 722 commuting zones (CZs) using its ZIP code (Tolbert and Sizer, 1996) and creating consistent NAICS industry identifiers across time using the concordance from Fort and Klimek (2016). We compute average wages as payroll per worker and deflate all values to 2015 dollars using the Bureau of Economic Analysis (BEA) Personal Consumption Expenditures (PCE) Price Index.

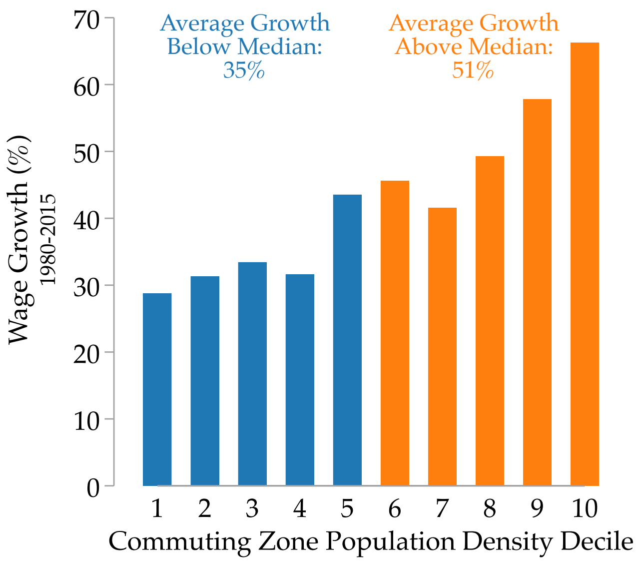
Since the LBD lacks data on the educational composition of workers, we use the US Decennial Census to examine educational patterns. To analyze the use of information technology, we rely on establishment-level surveys conducted by the US Census Bureau, as well as sector-level data from the Bureau of Economic Analysis's Fixed Asset Tables. We provide further details on these datasets below.

1.2 The Urban-Biased Growth Phenomenon

Since 1980, wage growth in the United States has systematically favored dense commuting zones, a pattern that we refer to as *urban-biased growth*. Figure 2 shows the strong positive relationship between wage growth and commuting zone population density between 1980 and 2015. Wages in the top decile of commuting zones in terms of population density (New York and Chicago) rose more than twice as fast as those in the bottom decile.[2] On average, wages increased by 51 percent in the "high-density" CZs above the median, compared to 35 percent in the "low-density" CZs below the median. As shown in Online Appendix 1.2, the urban-biased growth in Figure 2 led to a doubling of the wage-density gradient across commuting zones in the US economy.

[2]The pattern is nearly identical when commuting zones are ranked by population instead of density. The pattern is also not an artifact of using the LBD data: it holds in all major US labor market data sets, including the Quarterly Census of Employment and Wages (QCEW), the Decennial Census, and the American Community Survey (ACS). Online Appendix 1.2 provides these and other robustness exercises.

FIGURE 2: THE URBAN BIAS IN US WAGE GROWTH. 1980–2015



Notes: This figure shows wage growth from 1980 to 2015 across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density. Each decile represents one-tenth of the US population in 1980. The data come from the US Census Bureau's LBD. All values are inflation-adjusted to 2015 dollars using the BEA PCE price index.

In Online Appendix 1.2, we document two additional facts that narrow the set of plausible explanations for urban-biased growth. First, the pattern is not unique to the United States; it also appears in European data over the same period, suggesting that any explanation must apply across advanced economies. Second, it is largely absent in the postwar US economy before 1980, suggesting that the underlying mechanism must have emerged around that time.

1.3 Accounting for Urban-Biased Growth

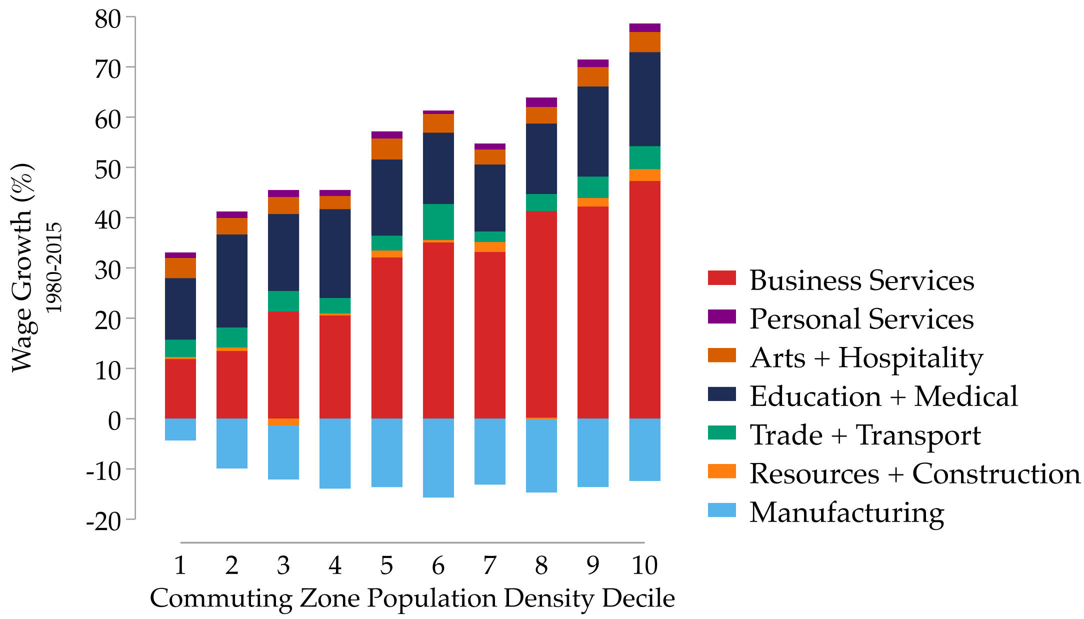
This section demonstrates that urban-biased growth is primarily a sectoral phenomenon, driven by large Business Services establishments.

The Role of Sectors. We develop a shift-share-style decomposition to understand the role of individual sectors in generating aggregate urban-biased growth. Let $w_{\ell s}$ denote the average wage in location ℓ and sector s, and let $\mu_{\ell s}$ denote the share of sector s in local employment. Then local average wages are given by $w_\ell = \sum_s \mu_{\ell s} w_{\ell s}$. We decompose local wage growth, defined as $g_\ell = (w_{\ell t+1} - w_{\ell t})/w_{\ell t}$, into additive sectoral contributions $\delta_{\ell s}$ as follows:

$$(1) \qquad g_\ell = \sum_s \delta_{\ell s} \quad \text{where} \quad \delta_{\ell s} := \frac{\mu_{\ell s t+1} w_{\ell s t+1} - \mu_{\ell s t} w_{\ell s t}}{w_{\ell t}}.$$

Each $\delta_{\ell s}$ captures the contribution of sector s to local wage growth, combining both changes in wages and changes in employment shares.

Figure 3: Sectoral Contributions to Urban-Biased Growth, 1980–2015



Notes: This figure shows wage growth between 1980 and 2015 across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density, and broken down into contributions from 1-digit NAICS industry groupings. Each decile accounts for one-tenth of the US population in 1980. The underlying data come from the US Census Bureau's LBD. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

Figure 3 shows the decomposition of CZ-level wage growth into sectoral components $\delta_{\ell s}$ for each decile of commuting zone density. The contribution of Business Services increases sharply with population density: in the top decile, the sector accounts for nearly two-thirds of all wage growth.[3] Most other sectors contribute evenly across space. Manufacturing is a notable exception, contributing negatively in all CZs, but less so in the least dense areas.

Next, we compute the *share* of urban-biased growth due to each sector. In particular, we define the share of the growth gap between high- and low-density CZs attributable to sector s as:

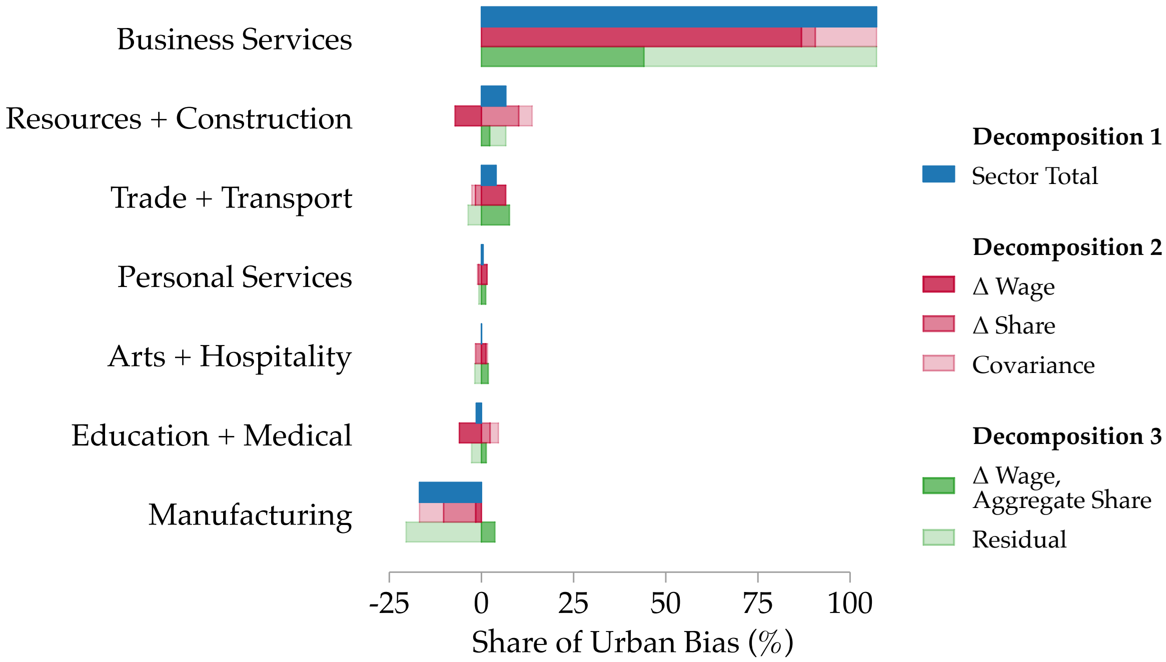
$$\Xi_s := \frac{\delta_{\ell' s} - \delta_{\ell s}}{g_{\ell'} - g_{\ell}} \quad \text{so that} \quad \sum_s \Xi_s = 1, \tag{2}$$

where ℓ' denotes commuting zones above the median density and ℓ those below.

Applying equation (2) formally reveals that Business Services account for the majority *share* of urban-biased growth. The blue bars in Figure 4 show the share of urban-biased growth explained by each sector, Ξ_s. The contribution of Business Services exceeds 100%, reflecting that the manufacturing sector contributes negatively, as its

[3]Figure 3 also shows that Business Services accounted for most of the overall wage growth in the US economy over this period. Figure OA.12 in the Online Appendix reports wage and employment growth across all NAICS 1-digit sectors from 1980 to 2015.

FIGURE 4: DECOMPOSING URBAN-BIASED GROWTH ACROSS SECTORS, 1980–2015



Notes: The figure decomposes the difference in wage growth from 1980 to 2015 between commuting zones with above- and below-median population densities in 1980 into the contributions of each sector. Blue bars show the contribution of each 1-digit NAICS sector to this overall gap (equation 2). Red bars decompose each sector's contribution into within-industry wage growth, across-industry employment reallocation, and a covariance term (equation 3). Green bars decompose each sector's contribution into a component due to wage growth differences under equalized sectoral employment shares across locations and a residual (equation 4). The data come from the US Census Bureau's LBD and include all private, non-farm employer establishments. High-density commuting zones are defined as those with the highest population densities jointly accounting for 50% of national employment in 1980. All values are adjusted to 2015 dollars using the BEA PCE price index.

decline occurred most quickly in the largest cities. The cumulative share accounted for by all other sectors is below 10%, just enough to offset the negative contribution of manufacturing.

All 2-digit industries within Business Services—Professional Services, Finance and Insurance, Information, Real Estate, Management of Companies, and Administrative Services—contributed positively to urban-biased growth. Figure OA.7 in the Online Appendix shows that the largest contributions came from Professional Services, Finance, and Information in that order.[4] Their substantial contribution to urban-biased growth arises from their large employment share combined with the strongly urban-biased wage growth within these sectors.

Equation (1) shows that a sector contributes to urban-biased growth either through

[4]Wage growth in Management of Companies (NAICS 55), which includes headquarters establishments, was also strongly urban-biased. This is consistent with recent research on headquarters growth and spatial inequality (Kleinman, 2022; Jiang, 2023). However, the industry's contribution to urban-biased growth was modest because the sector is small: in 2015, it represented only 2.4% of total US employment, compared to 26% for Business Services overall.

wage changes or shifts in its local employment share. To distinguish between these two channels, we further decompose the contribution of each sector, $\delta_{\ell s}$, as follows:

$$\delta_{\ell s} = \overbrace{\underbrace{\frac{\mu_{\ell st}\Delta w_{\ell st}}{\bar{w}_{\ell t}}}_{\Delta \text{ Wage}} + \underbrace{\frac{w_{\ell st}\Delta \mu_{\ell st}}{\bar{w}_{\ell t}}}_{\Delta \text{ Share}} + \underbrace{\frac{\Delta\mu_{\ell st}\Delta w_{\ell st}}{\bar{w}_{\ell t}}}_{\text{Covariance}}}^{\text{Decomposition 2}}. \tag{3}$$

where $\Delta w_{\ell st} = w_{\ell st+1} - w_{\ell st}$ and $\Delta \mu_{\ell st} = \mu_{\ell st+1} - \mu_{\ell st}$.

Combining equations (2) and (3), the red bars in Figure 4 show that the majority of urban-biased growth in Business Services reflects differential within-sector wage growth across space rather than differential sectoral reallocation. This reflects the relative stability of Business Services employment shares across CZs: in 1980, the sector employed 20% of US workers, 66% of whom were in CZs above the median density; by 2015, the figures were 26% and 61%, respectively.

Lastly, we investigate the role of differential spatial exposure to wage growth in explaining urban-biased growth. The first term in equation (3) reflects regional variation in sector-specific wage growth, but also spatial differences in initial sectoral specialization. To understand the role of such specialization differences, we isolate a term that captures each sector's counterfactual contribution to urban-biased growth in a world where industrial structure across CZs is equalized, but wage growth differences are as in the data:

$$\delta_{\ell s} = \overbrace{\underbrace{\frac{\bar{\mu}_{st}\Delta w_{\ell st}}{\bar{w}_{\ell t}}}_{\Delta \text{ Wage, Aggregate Share}} + \underbrace{\xi_{\ell st}}_{\text{Residual}}}^{\text{Decomposition 3}}, \tag{4}$$

where $\bar{\mu}_{st}$ is the share of employment of sector s in the aggregate economy and $\xi_{\ell st}$ is a residual term.

The dark green bars in Figure 4 represent the first term in equation (4), which isolates the contribution of wage growth differences between locations, abstracting from sectoral specialization. Comparison of the dark green bars with the dark red ones reveals that differences in exposure (initial sectoral composition) and differences in wage growth contributed roughly equally to urban-biased growth in Business Services. This finding is important: it shows that urban-biased growth is not solely a mechanical consequence of pre-existing specialization combined with aggregate sectoral trends. Instead, wage growth *within* Business Services varied systematically across commuting zones, accounting for nearly half of the observed urban bias.

The Role of Establishment Size. Are all Business Services establishments in high-density locations experiencing faster wage growth than their counterparts in less dense areas, or is the observed urban bias driven by a particular subset of establishments? In this section, we show that urban-biased wage growth is primarily driven by large Business Services establishments.

To this end, we divide establishments into two groups, each accounting for 50% of total US employment in 2015. Establishments with more than 108 employees fall into the "large" group.[5]

Following the decomposition in equation (2), we compute the share of urban-biased growth accounted for by large and small establishments within each sector. Figure 5 shows that large establishments account for nearly 80% of all urban-biased growth in Business Services.

Most of the urban-biased growth attributed to large Business Services establishments reflects differential wage growth across CZs rather than differential changes in their local employment shares, as shown by the red bars in Figure 5. The figure also shows that the decline in the employment shares of large establishments outside Business Services contributed negatively to urban-biased growth, reflecting the disproportionate disappearance of large well-paying manufacturing establishments in high-density locations.

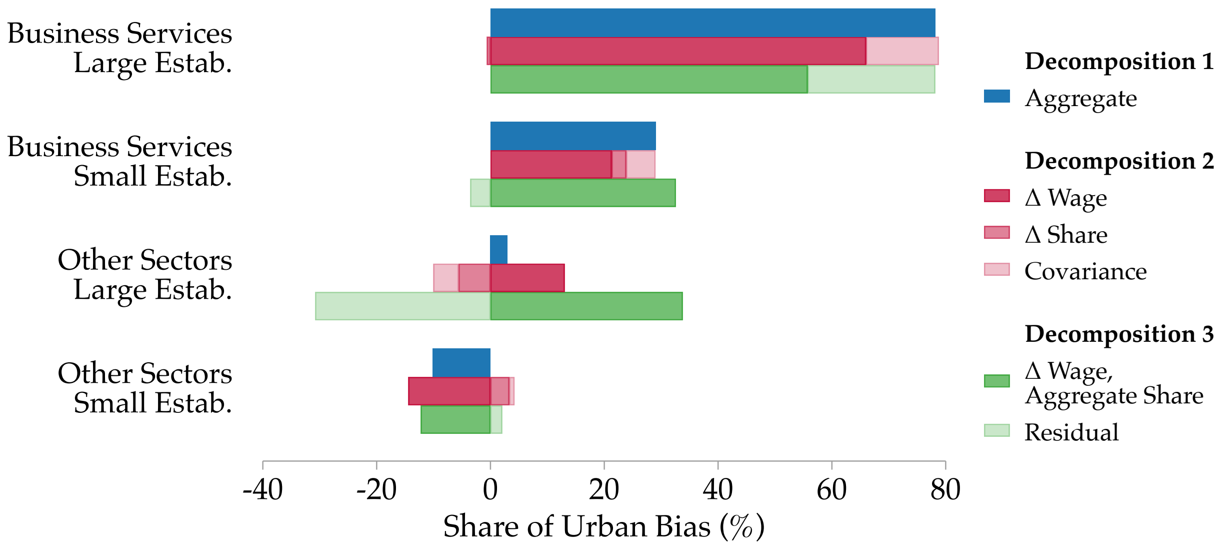
The prevalence of large establishments varies systematically across commuting zones. As shown in Figure OA.9 in the Online Appendix, their share of local employment increases sharply with the density of the commuting zone, while the share of small establishments remains flat. Outside of Business Services, large-establishment shares are largely stable across CZs of increasing density, and small-establishment shares decline with density.

Using the decomposition in equation (4), the dark green bars show that spatial wage growth differences among large establishments account for a larger share of urban-biased wage growth than the concentration of such establishments in dense areas. Within each size group, wage growth increases with density and this spatial gradient steepens with establishment size. Figure OA.9 illustrates this pattern directly: in Business Services, urban bias in wage growth is stronger for large establishments than for small ones, while in the residual sector, wage growth is largely uniform across both space and size.

The Role of Education. Many studies document the rise of the college wage premium and the increasing concentration of college-educated workers in large US cities since

[5]Each establishment belongs to a firm, and some firms operate multiple establishments. Results are robust to classifying size at the firm level: large Business Services firms typically operate large establishments (Online Appendix Figure OA.10).

FIGURE 5: DECOMPOSING URBAN-BIASED GROWTH ACROSS ESTABLISHMENTS, 1980–2015



Notes: The figure decomposes the 1980-2015 wage growth difference between commuting zones above and below median 1980 population density, by establishment size within each NAICS 1-digit sector. Blue bars show the share of the wage growth gap accounted for by each sector and establishment group combination (equation 2). Red bars further decompose these into within-industry wage growth, across-industry reallocation, and a covariance term (equation 3). Green bars use an alternative decomposition into wage growth under equalized sectoral employment shares and a residual (equation 4). Data come from the US Census Bureau's LBD and include all private, non-farm employer establishments. High-density CZs are those with the highest population densities jointly accounting for 50% of national employment in 1980. Large establishments are those comprising the top 50% of 2015 employment, with a threshold of 108 employees. All values are in 2015 dollars, deflated using the BEA PCE price index.

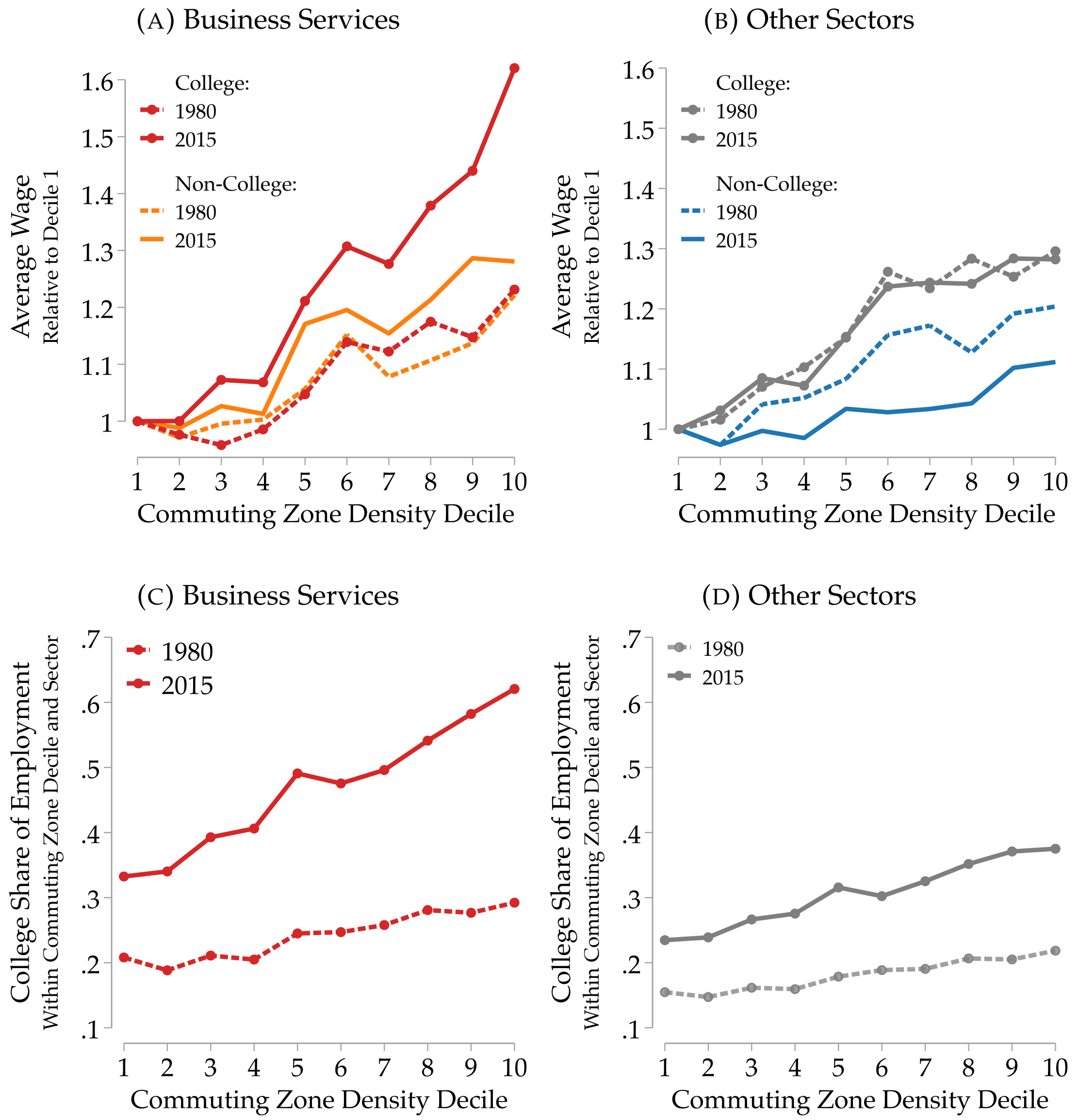
1980 (see, e.g., Glaeser and Salz, 2004; Diamond, 2016). In this section, we ask whether urban-biased growth is concentrated among a particular education group. It is not: more than half of college-educated Americans work outside Business Services, and this group experienced no urban-biased wage growth. At the same time, patterns within Business Services suggest the adoption of skill-biased technologies during this period.

The upper row of Figure 6 shows the wage growth by education group in each decile of commuting zone density, separately for Business Services and all other sectors. In Business Services, both college and non-college workers experienced urban-biased wage growth. Outside Business Services, neither group did.

At the same time, the *relative* wage of college workers rose more in dense cities in both sectors. However, outside of Business Services, this pattern reflects the disappearance of the urban wage premium for non-college workers (see also Autor, 2019), rather than urban-biased wage growth in levels for either group.

At the same time, college shares rose in an urban-biased way in both sectors, as shown in the bottom row of Figure 6. This shift amplified urban-biased growth in Business Services through two channels. First, because the rise in college share was faster in

FIGURE 6: EDUCATIONAL ATTAINMENT AND URBAN-BIASED GROWTH, 1980–2015

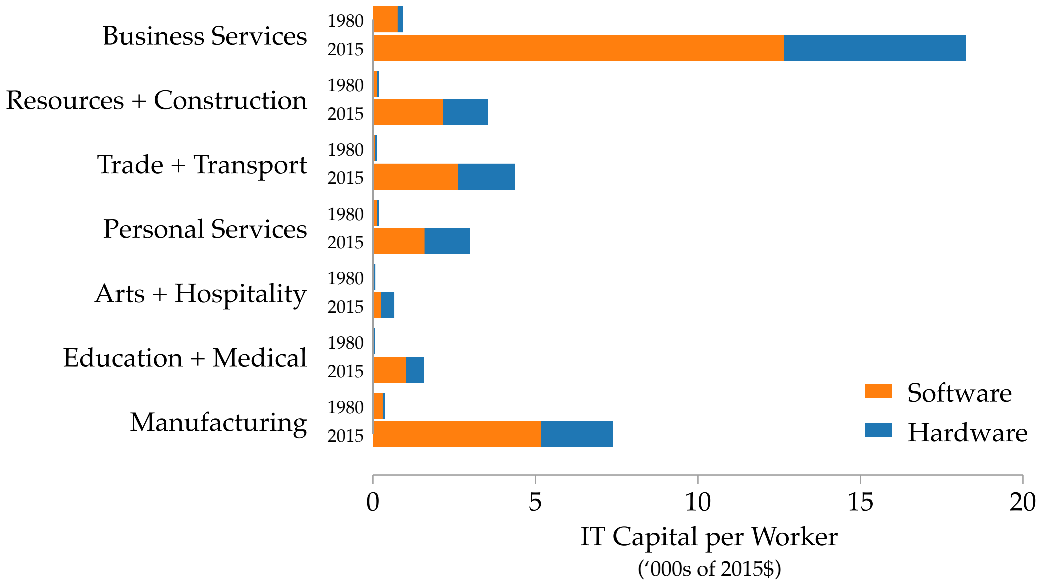


Notes: This figure shows average annual wages and college employment shares across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density, separately for Business Services and the rest of the economy in 1980 and 2015. Each decile accounts for one-tenth of the US population in 1980. The data come from the 1980 US Decennial Census and the 2015 American Community Survey.

denser locations, it tilted the workforce composition toward higher-wage workers more quickly in those areas. Second, since college-educated workers in Business Services experienced the strongest urban-biased wage growth, the shift toward this group further magnified the sector's contribution to the aggregate increase in the wage-density gradient.

The same change in the composition of the workforce explains why the wage-density gradient outside the Business Services remained flat, as shown in Figure 1. Although non-college workers in these sectors saw *rural*-biased wage growth, the rising share of higher-wage, college-educated workers offset this pattern. Without this shift toward

FIGURE 7: IT CAPITAL STOCK PER WORKER ACROSS SECTORS, 1980 AND 2015



Notes: The figure shows capital stock per worker for different information technology assets across 1-digit NAICS sectors in 1980 and 2015. Data on capital stock in each sector are from the BEA. Data on employment in each sector are from the Quarterly Census of Employment and Wages. Software refers to BEA capital asset codes ENS1–ENS3 and hardware to EP1A-EP31. Sectors appear in order of their contribution to urban-biased growth. All values are adjusted using the BEA's asset-specific capital-price deflators to 2015 dollars.

more educated workers, sectors outside of Business Services would have contributed negatively to urban-biased growth.

We draw two conclusions from these findings. First, urban-biased growth is a sectoral, not educational, phenomenon: all workers in Business Services saw urban-biased wage growth, while no workers outside the sector did.[6] Second, the co-movement of wages, college wage premia, and college shares in Business Services points to a form of skill-biased technical change that is stronger in dense places.

1.4 Toward a Mechanism: IT Capital and Business Services

In their seminal paper, Krusell et al. (2000) show that the decline in equipment capital prices can account for much of the increase in the college wage premium since 1980, given a complementarity between capital and skilled labor. Because skilled workers benefit more from cheaper capital under this complementarity, the wage gap between college and non-college workers widens as capital becomes cheaper.

Motivated by the skill-biased wage and employment growth within Business Services, we examine whether the same underlying shock can also explain the urban-biased wage growth observed in this sector. Our focus differs in one key respect: we focus on

[6]In Online Appendix 1.2, we replicate the analysis using occupational categories—cognitive non-routine versus all other occupations—and find nearly identical patterns.

TABLE 1: REGRESSIONS OF IT EXPENDITURE PER EMPLOYEE ON FIRM SIZE

	Log IT Software/Worker		Log IT /Worker	
	(1)	(2)	(3)	(4)
Log Sales	0.131	0.133	0.079	0.080
	(0.004)	(0.004)	(0.003)	(0.003)
Business Services × Log Sales	0.086	0.086	0.070	0.070
	(0.005)	(0.005)	(0.005)	(0.005)
Fixed Effects				
NAICS 6-digit x Year	✓	✓	✓	✓
CZ x Year	✓		✓	
CZ x Year × Business Services		✓		✓
Firm Age	✓	✓	✓	✓
Approx. No. of Observations	150,000		120,000	

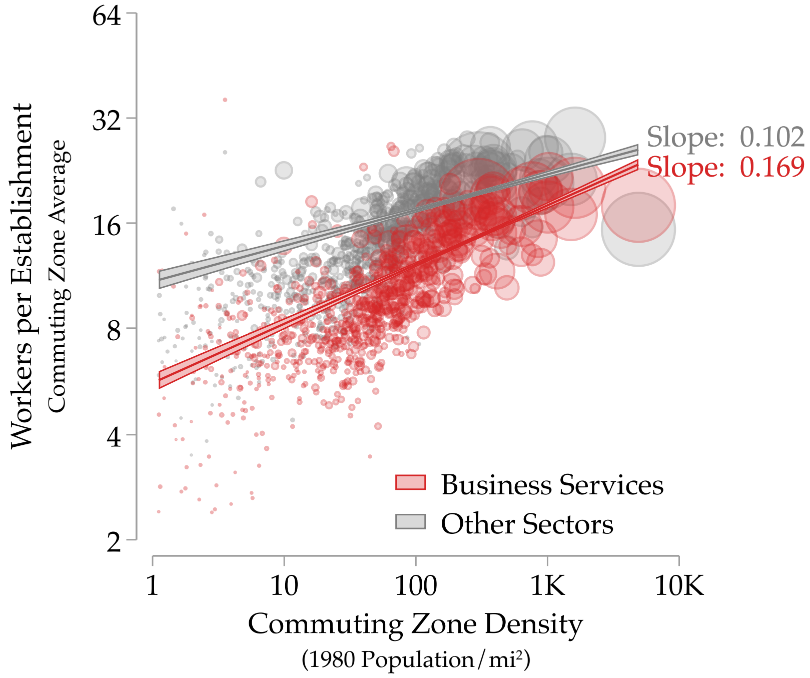
Notes: This table shows regressions of IT capital expenditures per worker on firm sales and firm location. Columns 1-2 use firms in the annual ACES survey from 2006–2015. Columns 3-4 use firms in the annual ICTS survey from 2004–2013. Employment is derived from the LBD. A firm's IT expenditures equal the value of its IT capital stock multiplied by the corresponding rental rates from the BLS, plus any non-capitalized IT expenses incurred during the period. We construct firm-level capital stocks using the perpetual inventory method applied to annual investment data from the ACES and ICTS. All regressions included fixed effects of the primary NAICS 6-digit industry interacted with year. We exclude firm-year observations missing data on sales, employment, payroll, or end-of-year capital assets. Observation counts rounded to comply with US Census disclosure rules.

information technology (IT) capital, a subcategory of equipment capital that accounts for most of the category's price decline during our sample period (see Figure OA.13 in the Online Appendix). This focus is motivated by the heavy use of IT capital by Business Services firms, which we document below.

While Krusell et al. (2000) emphasize a capital-skill complementarity, we highlight a complementarity between IT capital and firm scale that channels the gains from IT price declines toward large firms in dense cities through spatial variation in firm size. To motivate our focus on IT capital, we first show that Business Services firms are the most intensive users of IT capital in the US economy; something not true for other types of capital. We then present evidence for the capital-scale complementarity that is central to our mechanism by showing that IT capital intensity increases with firm size, especially within Business Services. This complementarity matters for urban-biased growth because firms in denser cities tend to be larger, particularly in Business Services, as we show at the end of this section.

We begin by comparing IT capital intensity across sectors. Using data from the BEA Fixed Asset Tables, Figure 7 plots IT capital stocks per worker in 1980 and 2015. Business Services was already the most IT-intensive sector in 1980, and by 2015, the gap had widened substantially: firms in the sector operated with nearly three times as much IT

Figure 8: Average Establishment Size across Commuting Zones and Sectors, 1980



Notes: The figure shows the average number of workers per establishment within each commuting zone (Tolbert and Sizer, 1996) and sector in 1980. The slope numbers indicate the coefficient on log commuting zone density in an employment-weighted regression of log average establishment size on the log commuting zone population density; the line shows the fitted regression lines with 95% confidence intervals. Circle size is proportional to commuting zone population. The underlying data comes from the Quarterly Census of Employment and Wages published by the US Bureau of Labor Statistics.

capital per worker as the next most intensive sector.[7] The concentration of IT capital in Business Services makes the secular decline in IT prices a natural candidate to explain the wage growth in the sector.

Next, we provide direct empirical evidence of a capital-scale complementarity and document its particular strength in Business Services. We use firm-level investment data from the Annual Capital Expenditures Survey (ACES) and the Information and Communication Technology Survey (ICTS) to construct software and hardware capital stocks using the perpetual inventory method, deflating observed investments using asset-specific price indices (following Lashkari et al., 2024). We then combine these capital stocks with detailed rental rate data from the Bureau of Labor Statistics (BLS) to compute total annual payments to IT capital for each firm. Firm-level employment and payroll data are drawn from the Longitudinal Business Database (LBD). The ACES only reports software investments separately, while the ICTS distinguishes both software and hardware from other types of equipment capital. For robustness, we report our results using both definitions of IT capital.[8]

[7] In the Online Appendix, we also show that Business Services do not differ markedly from other sectors in their use of non-IT capital.

[8] See Online Appendix B.5 for details on data construction, sample selection, and additional discussion

Table 1 presents the results of the regressions of log capital payments per worker on log sales, controlling for industry-by-year and firm-age fixed effects. Columns 1-2 define IT capital as software only; Columns 3-4 use the combined software and hardware measure. Columns 1 and 3 include commuting zone-by-year fixed effects, while Columns 2 and 4 further interact these with a Business Services indicator. These location-sector fixed effects help isolate the role of firm size by controlling for productivity and factor price differences across regions and sectors.

The results show that IT capital per employee rises steeply with firm size in Business Services, while the relationship is much weaker in other sectors. The effect is stronger for software (Columns 1 and 2) than for total IT capital (Columns 3 and 4), though the cross-sector difference in slope is consistent across definitions. We interpret these results as suggestive evidence of an IT capital-scale complementarity in production.

The relationship between capital-labor ratios and firm size in Table 1 closely mirrors the findings of Lashkari et al. (2024), who document similar patterns using French firm-level data. Their estimated correlations are stronger than ours: in a specification without firm fixed effects but otherwise similar controls, they report coefficients on log sales in the range of 0.4 to 0.6; when they include firm fixed effects, they find elasticities between 0.15 and 0.27—very close in magnitude to the findings in Table 1.

A capital-scale complementarity amplifies the exposure of high-density locations to declines in IT capital prices because average establishment size increases with local population density.[9] Figure 8 plots average employment per establishment against population density across commuting zones, separately by sector, using data from the Quarterly Census of Employment and Wages (QCEW). The size-density gradient is positive in both sectors but is almost twice as steep in Business Services as in the rest of the economy. In 1980, the elasticity of establishment size with respect to density was 0.17 in Business Services and 0.10 in other sectors.

2. Theory

We begin by showing in a general spatial model of production how a capital-scale complementarity leads to urban-biased wage growth as IT capital becomes cheaper. In a second step, we embed this mechanism in a dynamic spatial model that is suitable for estimation and counterfactual analysis. All derivations are provided in Online Appendix 2.1.

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and robustness checks. Online Appendix B.5 also situates our findings in relation to complementary results in Lashkari et al. (2024) and Jiang (2023).

[9] We measure firm size using employment rather than sales, since sales data are unavailable at the location-sector level.

2.1 Capital-Scale Complementarities and Urban-Biased Growth

We consider a standard spatial economy with a finite set of discrete locations ℓ and sectors s, where production uses labor and capital. Labor is subject to reallocation frictions, so that equilibrium wages, $w_{\ell s}$, may vary across location-sector pairs. In contrast, capital is freely mobile across space and sectors, so a single national rental rate R prevails. Locations and sectors differ in two exogenous shifters: a labor demand shifter $A_{\ell s}$ ("productivity") and a labor supply shifter $B_{\ell s}$ ("amenity"). The economy is static and all trade is free.

Firm-Level Production. Intermediate input firms in each location and sector produce differentiated varieties. A firm in location ℓ and sector s can produce y units of its variety at total cost:

$$C(w_{\ell s}, R, y; A_{\ell s}) = yV(w_{\ell s}/A_{\ell s}, R, y) + E(w_{\ell s}, R),$$

where V denotes unit variable costs and E denotes an entry cost required to start production. Note that the variable cost aggregator V may be non-homothetic, so that both the level and composition of unit variable costs can vary with firm scale, y.

We define the *scale elasticity*, ϵ_{KL}, as the output elasticity of the firm's capital-labor ratio:

$$\epsilon_{KL} := \frac{\partial \log K/L}{\partial \log y} = \frac{C_{Ry}y}{C_R} - \frac{C_{wy}y}{C_w},$$

where C_x denotes the partial derivative of total cost with respect to variable x and C_{xy} the cross-partial with respect to variables x and y.

The scale elasticity captures the capital-scale complementarity central to our mechanism. It is zero if and only if the entry and variable cost functions are homothetic and identical. It is non-zero whenever entry and operating costs differ in capital intensity. In that case, the capital-labor ratio varies with firm scale y.

A representative final goods producer aggregates intermediate inputs into a numeraire consumption good using a nested CES production function. The substitution elasticity between varieties within a sector is ι_s; across sectors, it is γ. Intermediate input firms therefore face a revenue function of the form $\mathcal{Q}_s y^{\zeta_s}$, where $\zeta_s \in (0,1)$ captures the curvature of demand and $\mathcal{Q}_s$ is an endogenous shifter of aggregate sectoral demand.

A competitive fringe of potential entrants drives profits net of entry costs to zero, ensuring that the following *free entry condition* holds in each location and sector in equilibrium:

$$\max_y \{\mathcal{Q}_s y^{\zeta_s} - C(w_{\ell s}, R, y; A_{\ell s})\} = 0. \tag{5}$$

Importantly, given aggregate sectoral demand, Q_s, and the capital rental rate, R, the free entry condition determines equilibrium wages in each location-sector, *independently of labor supply*. Labor markets clear at the wage required to satisfy the free entry condition through adjustments in the endogenous number of firms in each location-sector, $N_{\ell s}$.[10]

This structure suffices to characterize how changes in the capital rent rate affect wages across locations and sectors. Since cross-sectional wage variation is pinned down by the free entry condition, we do not specify labor supply or the determination of aggregate quantities or prices for now. We close the model in the next section.

IT Capital Rental Rates and Urban-Biased Growth. We study the conditions under which falling IT capital rental rates lead to stronger wage growth in denser locations.[11] Transmission operates through the free entry condition. Totally differentiating this condition, applying the envelope theorem, and rearranging terms yield the following:

$$\text{(6)} \qquad \frac{d\log w_{\ell s}}{d\log R} = -\Lambda_{\ell s} + (1+\Lambda_{\ell s})\frac{d\log Q_s}{d\log R} \quad \text{where} \quad \Lambda_{\ell s} := RC_R/w_{\ell s}C_w.$$

The "exposure" term, $\Lambda_{\ell s}$, is defined as the ratio of capital to labor payments at firms in location-sector (ℓ, s). It captures all variation in wage responses to changes in the rental rate of capital across locations and sectors.

The intuition behind equation (6) is straightforward: a decline in capital rental rates increases operating profits for all firms that use capital. In response, entry and firm expansion raise wages until profits net of entry costs are again zero. When capital intensity is high, cost savings are greater and wages must rise more to offset them. In addition, declines in capital rental rates also raise aggregate demand, further increasing profits. In locations where labor is a small share of costs, wages must rise more to offset the same increase in profits.

We characterize how exposure $\Lambda_{\ell s}$ varies with location productivity to a first-order as one moves from less to more productive locations:

$$\text{(7)} \qquad \frac{d\log \Lambda_{\ell s}}{d\log A_{\ell s}} = \underbrace{(\sigma_{KL}-1)\frac{d\log w_{\ell s}}{d\log A_{\ell s}} - \sigma_{KL}^V}_{\text{Neoclassical}} + \underbrace{\epsilon_{KL}\frac{d\log y}{d\log A_{\ell s}}}_{\text{Scale}}.$$

Here, σ_{KL} and σ_{KL}^V are the substitution elasticities between capital and labor in total and variable cost.

[10] In the case of free labor mobility, this implies that all production occurs in the most productive location. Frictional labor mobility across locations and sectors sustains an equilibrium with non-degenerate distribution of employment across locations and sectors.

[11] The shock we study is the decline in the investment price of IT capital. These declines translate into lower rental rates, which are the relevant prices for firms. In the quantitative model below, we explicitly model this link by introducing capitalists who invest in IT capital and rent it to firms.

The *neoclassical terms* reflect standard price and substitution effects: higher productivity raises wages, which shifts cost shares toward labor and away from capital when $\sigma_{KL} < 1$. At the same time, higher labor productivity leads to substitution toward labor for as long as $\sigma_{KL}^V \neq 0$. All these forces tend to *lower* exposure in more productive places.

The *scale term* captures the core mechanism of our paper. When the complementarity between capital and firm scale is positive ($\epsilon_{KL} > 0$) and firm size increases with productivity, the scale channel amplifies exposure in more productive locations. In contrast, when $\epsilon_{KL} = 0$, this channel is shut down and only the neoclassical effects remain, which predict a decline in exposure with productivity. When $\epsilon_{KL} > 0$, whether the scale channel dominates the neoclassical channel is a quantitative question.

We now characterize how wages and firm size change with productivity in the cross-section of locations. From the free entry condition, Shephard's Lemma, and the envelope theorem:

$$\frac{d \log w_{\ell s}}{d \log A_{\ell s}} = 1 - \phi_{\ell s}^E, \tag{8}$$

where $\phi_{\ell s}^E$ is the share of the firm's labor in entry as opposed to variable production.

When entry costs depend only on capital ($\phi_{\ell s}^E = 0$), they are constant across space. In this case, productivity advantages are fully arbitraged away: firms enter until wages rise enough to offset productivity differentials. Marginal costs equalize across locations, firm size is uniform, and wages rise one-for-one with productivity in the cross-section.

When $\phi_{\ell s}^E > 0$, entry costs increase as wages get bid up in productive locations. This limits arbitrage: if all productivity gains were competed away, no firm would enter given the higher entry costs. As a result, marginal costs remain lower in more productive areas, firms operate at larger scale, and wages rise less than one-for-one with productivity.[12]

In summary, a decline in IT capital rental rates leads to stronger wage growth in high-exposure places. Exposure rises with productivity whenever ϵ_{KL} is large enough and $\phi_{\ell s}^E > 0$ holds. Whether this implies *urban*-biased wage growth depends on how productivity varies with density in the cross-section of locations.[13]

Proposition 1 (Urban-Biased Growth and IT Rental Rates). *Suppose the following conditions hold for sector s:*

i. The wage elasticity of entry costs is positive, so that $\phi_{\ell s}^E > 0$.

[12] The firm's first-order condition with respect to output is $Q_s \zeta_s y^{\zeta_s - 1} = C_y$. This implies that optimal output y is higher in locations with lower marginal cost C_y. This result holds as long as marginal cost does not fall with wages and increasing returns are not too strong (see Appendix 2.1).

[13] Population density is an equilibrium outcome shaped by the interaction of labor supply, land supply, and labor demand shifters. Thus, any observed correlation between productivity and density reflects underlying correlations between these fundamental determinants.

ii. The capital-scale complementarity is sufficiently strong, so that $\epsilon_{KL} \gg 0$.
iii. Labor productivity is positively correlated with population density across locations.

Then a decline in the rental rate of capital induces a positive correlation between wage growth and population density in the cross-section of locations.

If productivity itself is a function of local density, this creates an amplification mechanism. As wages rise in some locations, workers move in, raising density, and hence productivity, which further raises wages. We allow for such amplification effects in our quantitative analysis below.

Discussion. Our mechanism combines three insights. First, when entry costs rise with productivity—for example, because entry raises wages and entry costs involve labor—high-productivity locations retain lower marginal costs in equilibrium, allowing firms to operate at larger scale. Second, if larger firms tend to be more capital-intensive, these spatial differences in firm size translate into greater capital intensity in more productive locations. Third, the impact of falling capital rental rates depends on a firm's capital-to-labor cost share, making productive, capital-intensive locations more exposed to such shocks under certain parameter conditions (see Proposition 1).

Our mechanism is not sector-specific. Sectoral variation arises only through differences in parameter values, including those highlighted by Proposition 1. This is a strength of our approach: in the calibration below, all sectoral differences reflect differences in empirical moments, not structural modeling assumptions.

The mechanism also does not hinge on a specific interpretation of capital. While we focus on IT assets, any capital good can produce urban- or rural-biased growth. What matters are the key elasticities highlighted above, and their interaction with local characteristics.

The argument extends to models with multiple local factors, such as land or heterogeneous labor. In such settings, the free entry condition continues to determine the average cost of all local inputs, regardless of individual supply elasticities. As long as some local factor enters the entry cost, more productive locations require firms to scale up as the factor becomes congested. When capital and scale are complements, this implies a higher capital intensity in more productive locations.

2.2 Quantitative Implementation

We embed the above mechanism into a dynamic quantitative framework suitable for estimation and counterfactual analysis. The quantitative model features several *local* production factors: two types of labor (high- and low-skilled) and commercial land. It allows for firm heterogeneity and imposes functional forms for variable and entry production functions. We also introduce a class of capitalists who own all non-labor factors and make savings and investment decisions across time periods indexed by t (Kleinman et al., 2023; Walsh, 2025).

Production and Market Structure. We use the nested CES production function from Krusell et al. (2000), which allows different substitution elasticities between capital and high- and low-skill labor. To capture the capital-scale complementarity central to our mechanism, we adopt a one-parameter non-homothetic extension introduced by Lashkari et al. (2024). This extension nests the specification from Krusell et al. (2000) as a special case and provides a tractable way to parameterize the capital-scale complementarity.[14]

The resulting production function yields a parsimonious variable cost function that flexibly accommodates both scale effects and variation in capital-labor substitution patterns across skill types:

$$V_s(z; \frac{w^H_{\ell st}}{A^H_{\ell st}}, \frac{w^L_{\ell st}}{A^L_{\ell st}}, \frac{R_t}{A^K_{st}}, y) = yz^{-1} \left(\left((\frac{w^H_{\ell st}}{A^H_{\ell st}})^{1-\sigma_s} y^{\bar{\epsilon}_s} + (\frac{R_t}{A^K_{st}})^{1-\sigma_s} \right)^{\frac{1-\varphi_s}{1-\sigma_s}} + (\frac{w^L_{\ell st}}{A^L_{\ell st}})^{1-\varphi_s} \right)^{\frac{1}{1-\varphi_s}},$$

where z denotes firm-level total factor productivity; $w^H_{\ell st}$ and $w^L_{\ell st}$ are the wages of high- and low-skill labor in location ℓ and sector s; $A^H_{\ell st}$ and $A^L_{\ell st}$ are location-sector productivity shifters for high- and low-skill labor. The term A^K_{st} is a sector-specific productivity shifter for IT capital.[15] The substitution elasticities between capital and high- and low-skill labor are σ_s and φ_s, and $\bar{\epsilon}_s$ indexes the non-homotheticity.

The non-homotheticity parameter $\bar{\epsilon}_s$ captures the strength of the capital-scale complementarity.[16] When $\bar{\epsilon}_s \neq 0$, the capital-labor ratio in variable costs varies with firm scale, y. When $\bar{\epsilon}_s = 0$, the function collapses to the standard homothetic CES case studied by Krusell et al. (2000), and capital intensity in variable costs is independent of firm scale.

The non-homothetic CES production function offers a tractable way to model scale-dependent technologies (see also Lashkari et al., 2024). Like its homothetic counterpart, it can be microfounded. Trottner (2022) shows that this functional form arises naturally when firms choose among production technologies that trade off fixed and

[14] Note that part of the capital-scale complementarity arises from factor intensity differences across variable and entry costs; the non-homotheticity in variable production adds to this.

[15] Other forms of capital are absorbed into the productivity shifters $A^H_{\ell st}$, $A^L_{\ell st}$, and A^K_{st}; incorporating them explicitly would not alter the logic of our mechanism.

[16] To see this, consider the marginal rate of technical substitution between high-skill labor and capital:

$$\frac{dy/dh}{dy/dk} = \left(\frac{k}{h} \frac{A^H_{\ell st}}{A^K_{st}} \right)^{\frac{1}{\sigma_s}} y^{\frac{\bar{\epsilon}_s}{\sigma_s}}.$$

When $\bar{\epsilon}_s < 0$, the substitution rate falls with output, so larger firms shift the composition of their inputs toward capital.

marginal costs, with more capital-intensive methods involving higher fixed costs (see also Lashkari et al., 2024). Larger firms adopt these technologies because they can spread fixed costs over more units of output. We interpret the non-homothetic CES specification as a reduced-form representation of how fixed and variable cost differences shape the relationship between capital intensity and firm scale.

In our quantitative implementation, entry costs depend on the rental rate of commercially zoned land, $r^C_{\ell st}$, and the price of the numeraire good:

$$E_s(1, r^C_{\ell st}) = \tau_s (r^C_{\ell st})^{\eta_s}, \tag{9}$$

where τ_s is a sectoral scale parameter and $\eta_s \in (0,1)$ is the share of expenditures on commercially zoned land.

The functional form in equation (9) preserves the core logic of our mechanism. When entry costs include a local factor, they rise with firm entry in productive locations. As a result, not all marginal cost advantages are arbitraged away in equilibrium: otherwise, no firm would enter given elevated costs. This incomplete arbitrage allows firms to operate at larger scale in more productive locations.[17] When $\eta_s = 0$, entry costs are constant across space, and productivity advantages are fully offset by higher local factor prices. As η_s increases, entry costs rise more steeply with local factor prices, generating a stronger positive relationship between firm scale and productivity across space.

After paying the sunk entry cost, firms draw their productivity $z \in (1, \infty)$ from a Pareto distribution with scale parameter 1 and shape parameter ν:

$$\Omega(z) := 1 - z^{-\nu} \quad \text{where} \quad z > 1.$$

Because entry costs are sunk, firms cannot condition their decision on the realized draw, ruling out selection on entry consistent with the empirical evidence in Combes, Duranton, Gobillon, Puga, and Roux (2012). Firms exit at a common rate ξ in each location-sector, in line with the empirical evidence in Walsh (2025).

In the quantitative model, the free entry condition reflects the expectations of firms at the time of entry: entrants learn their idiosyncratic productivity z only after paying entry costs and face an exogenous exit probability each period. Entry occurs when the expected present value of profits equals the entry cost:

$$\int \mathcal{V}_{\ell st}(z) d\Omega(z) = E_s(1, r^C_{\ell st}),$$

[17] We abstract from labor in entry costs because our identification strategy can discipline the share of only one local factor. We exclude IT capital for quantitative reasons: if it entered entry costs, the large observed decline in IT prices would have substantially lowered entry costs and reduced firm size—contrary to the data.

where $\mathcal{V}_{\ell st}(z)$ is the present-discounted value of a firm with productivity z in location ℓ, sector s and time t.

Labor Supply. Within each location-sector, workers of type $f \in \{H, L\}$ choose consumption of the final good and housing to maximize a Cobb-Douglas utility function with housing share α^f, subject to their income $w^f_{\ell st}$.

Idiosyncratic preferences over locations and sectors give rise to upward-sloping labor supply curves into each location-sector. Location-specific preference shocks follow a Fréchet distribution with a shape parameter ϱ^f_1 and an inverse scale parameter $\bar{B}^f_{\ell t}$. Conditional on location, sector-specific shocks are drawn from a Fréchet distribution with shape parameter ϱ^f_2 and inverse scale $B^f_{\ell st}$. Workers first draw a location-specific shock and, upon arrival, draw sector-specific productivity shocks.

These assumptions yield standard expressions for the share of type-f workers selecting location ℓ, denoted $\lambda^f_{\ell t}$, and the share selecting sector s within a location, denoted $\mu^f_{\ell st}$:

$$\lambda^f_{\ell t} = \frac{\bar{B}^f_{\ell t}(r^{-\alpha^f}_{\ell t}\,\omega^f_{\ell t})^{\varrho^f_1}}{\sum_{\ell'} \bar{B}^f_{\ell' t}(r^{-\alpha^f}_{\ell' t}\,\omega^f_{\ell' t})^{\varrho^f_1}}, \qquad \mu^f_{\ell st} = \frac{B^f_{\ell st}(w^f_{\ell st})^{\varrho^f_2}}{\sum_{s'} B^f_{\ell s' t}(w^f_{\ell s' t})^{\varrho^f_2}}, \tag{10}$$

where $\omega^f_{\ell t} := \left(\sum_s B^f_{\ell st}(w^f_{\ell st})^{\varrho^f_2}\right)^{1/\varrho^f_2}$ captures the expected wage of workers of type f in location ℓ and $r_{\ell t}$ denotes the rental rate of residential housing.

The national stock of type-f labor is exogenously fixed at $\bar{L}^f_t$, so the total number of type-f workers in a location-sector pair is given by $L^f_{\ell st} = \lambda^f_{\ell t}\mu^f_{\ell st}\bar{L}^f_t$.

Investment Decisions and Factor Ownership. A unit mass of identical, atomistic capitalists makes all dynamic investment decisions in the economy. Capitalists own all firms, capital, commercially zoned land, and residential housing. They choose consumption of the final good, investment in capital, and the creation of new firms in each location-sector and at each point in time to maximize utility, subject to the constraints of the economy described below:

$$\max_{\{C_t\},\{K_{t+1}\},\{N_{\ell st+1}\}} \sum_{t=0}^{\infty} \beta^t \log(C_t) \tag{11}$$

subject to a set of period budget constraints:

$$C_t + p_t(K_{t+1} - (1-\delta_t)K_t) + \sum_{\ell,s} E(1, r^C_{\ell st})(N_{\ell st+1} - (1-\xi)N_{\ell st}) = R_tK_t + \sum_{\ell,s} r^C_{\ell st}\bar{X}^C_{\ell s} + \sum_{\ell} r_{\ell t}\bar{X}^R_{\ell} + \sum_{\ell,s}\Pi_{\ell st},$$

where $\beta \in (0,1)$ is the discount factor. The variables $\bar{X}^R_{\ell}$ and $\bar{X}^C_{\ell s}$ denote the stocks of residential housing and commercially zoned land, respectively, while $\Pi_{\ell st}$ represents the total variable profits of firms in location ℓ and sector s. The term p_t denotes the investment price of capital and δ_t its depreciation rate.

A representative firm transforms the numeraire good into capital at an exogenous rate $\mathcal{Z}_t$, so that $p_t = 1/\mathcal{Z}_t$. The evolution of $\mathcal{Z}_t$ captures investment-specific technical change in our model, which drives all changes in the investment price of capital.

The economy begins in period $t = 0$ with an initial capital stock K_0 and a distribution of firms $\{N_{\ell s0}\}$ across location-sector pairs. All asset holdings are required to be nonnegative.

Equilibrium. *An equilibrium is a set of time paths for factor prices* $\{w^f_{\ell st}, R_t, r^C_{\ell st}\}$*; rental rates for residential housing* $\{r_{\ell t}\}$*; the investment price of capital* $\{p_t\}$*; capitalist consumption* $\{C_t\}$*; the aggregate capital stock* $\{K_t\}$*; the number of firms* $\{N_{\ell st}\}$*; and local labor supplies* $\{L^f_{\ell st}\}$*; such that in each period:*

i. *Capitalists solve the problem in equation* (11)*.*
ii. *Workers make location and sectoral choices according to equation* (10)*.*
iii. *Labor markets clear in every location, sector, and for each worker type.*
iv. *The investment and rental markets for capital clear.*
v. *Residential housing and commercially zoned land markets clear in every location.*
vi. *The national market for the final good clears.*

A *steady-state equilibrium* is an equilibrium in which all prices and allocations remain constant over time.

Recovering the Mechanism. The urban-biased growth mechanism summarized in Proposition 1 continues to hold in the quantitative model. The key difference is that, rather than pinning down wages alone, in the quantitative model the free entry condition determines a cost-share-weighted average price of all *local* factors used in production—namely, high- and low-skill labor and commercially zoned land. Prices of each individual factor may vary with local supply conditions, but their cost-share-weighted average adjusts to equate variable profits and entry costs in each location and sector.

Correspondingly, the exposure term for each location-sector captures total IT capital payments relative to total payments to local factors. Moreover, the exposure term now reflects the ratio of these payments at the *average* firm in each location-sector. We summarize this result in the following theorem.

Theorem 1. *Consider the economy described above. In steady state, the response of the cost-share-weighted average price of local factors,* $\bar{w}_{\ell s}$*, to a change in the rental rate of capital is* *given by:*

$$\frac{d\log \bar{w}_{\ell s}}{d\log R} = -\Lambda_{\ell s} + (1+\Lambda_{\ell s})\frac{d\log Q_s}{d\log R} \quad \text{where} \quad \Lambda_{\ell s} := \frac{\Phi^K_{\ell s}}{\Phi^L_{\ell s}}. \tag{12}$$

where $\Phi^K_{\ell s}$ and $\Phi^L_{\ell s}$ denote the expected present-discounted values of a firm's total lifetime payments to capital and to local factors, respectively, in location-sector (ℓ, s) prior to entry.

This generalizes the result in equation (6) to a setting with multiple local factors, heterogeneous firms, and dynamic capital accumulation. We prove a more general version of Theorem 1 with arbitrary inputs in Online Appendix A.2.

As before, firm entry raises local factor prices more in more productive location-sector pairs, raising entry costs, and forcing firms to operate at larger scale to break even. When firm scale and capital are complementary, larger scale leads firms in more productive locations to adopt more capital-intensive production methods. As a result, these firms are more exposed to changes in the price of capital. Consequently, wages and other local factor prices in high-productivity locations respond more strongly to capital price movements—generating urban-biased growth when productivity and population density are positively correlated.

3. Quantification

To move toward the quantification of our mechanism, this section discusses how we calibrate the key elasticities of the model and infer its location- and sector-specific productivity and amenity terms.

3.1 Quantifying the Model

We calibrate the model to the US economy from 1980 to 2015 at an annual frequency. Locations correspond to the 722 commuting zones (CZs) that cover the continental United States, as defined by Tolbert and Sizer (1996). Industries are grouped into two sectors: Business Services and a residual sector comprising all other private, non-agricultural employment. We classify workers as college-educated if they hold at least a four-year degree, and as non-college otherwise.

We construct an annual panel of wages and employment across CZs, sectors, and education levels by interpolating decadal data from the US Decennial Census and the American Community Survey (ACS), accessed via IPUMS (Ruggles, Genadek, Goeken, Grover, and Sobek, 2017). We use the same data to construct CZ-level rental rates for each year. We obtain sector-level data on IT capital prices, depreciation rates, and capital stocks by sector from the BEA Fixed Asset Tables.

We estimate the key elasticities governing the strength of our mechanism by targeting a set of cross-sectional moments. Although most parameters are estimated jointly as part of an equilibrium-calibration loop, we describe each in terms of the moments that are most informative for its identification. Given the parameter values, we recover the time path of structural residuals that allows the model to match observed wages and employment across commuting zones, sectors, education groups, and years, along with residential rents, IT capital prices, and capital stocks. Table 2 lists all time-invariant structural parameters and time-varying structural residuals. Note that our calibration strategy does not assume that the model is in a steady state.

Non-Homotheticity ($\bar{\epsilon}_s$) and Factor Substitution Elasticities (σ_s, φ_s). The non-homotheticity parameter $\bar{\epsilon}_s$ governs how capital intensity varies with firm scale within a location-sector. Since firm productivity is factor-neutral and all input price and productivity variation occurs at the location-sector level, differences in relative factor demand among incumbent firms *within* a location-sector arise only if $\bar{\epsilon}_s \neq 0$.[18] Once $\bar{\epsilon}_s \neq 0$, the capital-scale relationship depends not only on $\bar{\epsilon}_s$, but also on the elasticities of substitution between capital and high-skill labor (σ_s), and between low-skill labor and the capital-high-skill bundle (φ_s).[19]

This observation motivates our identification strategy. We choose $\bar{\epsilon}_s$ to match how capital-labor ratios vary with firm sales *within* each location-sector. Table 1 shows a strong positive correlation in the data, particularly in Business Services. We replicate this regression in the model-generated data and choose $\bar{\epsilon}_s$ to match the sector-specific slope coefficients in Table 1. The resulting values for $\bar{\epsilon}_s$ are -0.18 for Business Services and -0.07 for the residual sector.

Given that $\bar{\epsilon}_s \neq 0$ in both sectors, the ratio of high- to low-skill labor varies systematically with the size of the firm. We exploit this variation to identify φ_s. Specifically, using data from the US Census' Current Population Survey in 1992, we regress the college share of employment on log firm size as measured by firm employment (cf. Figure OA.14 in the Online Appendix). In the model, we run the same regression in the same year and choose φ_s to match the coefficients on log sales. This yields φ_s of 1.24 for Business Services and 1.57 for the residual sector, implying moderate substitutability between education groups.

Finally, we impose $\sigma_s = \sigma$ and calibrate it to match the aggregate substitution elasticity between IT capital and labor, targeting the estimate of 0.95 in Lashkari et al. (2024). We find $\sigma = 0.55$, which implies a strong complementarity between IT capital and high-skill labor at the firm level. Since $\sigma < \varphi_s$ holds for our estimates, production exhibits capital-skill complementarity, consistent with Krusell et al. (2000), and this

[18]The overall scale elasticity in the model also reflects differences in capital intensity between variable and entry costs relevant for firm entry.

[19]Online Appendix A.2.2 shows this explicitly.

complementarity is stronger in Business Services.

Entry cost parameters (η_s, τ_s). The parameter η_s captures the share of commercially zoned land in entry costs. As shown in Section 2.1, firm scale is invariant across space when entry costs are fully denominated in nationally-priced inputs; that is, when $\eta_s = 0$. In contrast, when $\eta_s > 0$, entry costs rise with local factor prices, and firm scale increases with location productivity.

As we show below, average labor productivity is strongly correlated with population density across locations, especially in Business Services. This implies that local factor prices tend to be higher in more densely populated areas, as required by our mechanism. We estimate η_s by matching the cross-sectional relationship between population density and average employment per establishment across commuting zones (see Figure 8). We find a value for η_s of 0.18 in Business Services and of 0.14 in the residual sector, reflecting the steeper size-density gradient in Business Services.

The parameter τ_s determines the average firm size in the entire economy in sector s. We calibrate it to match the average number of employees per establishment in 1980, separately for each sector.

Labor Supply Elasticities, ϱ_1^f and ϱ_2^f. For each education group, labor supply elasticities determine how local demand shifts affect wages versus employment. We estimate two elasticities: the sectoral elasticity ϱ_2^f, which governs how easily workers move across sectors within a commuting zone, and the spatial elasticity ϱ_1^f, which governs how easily the move across space. We estimate both elasticities outside the equilibrium calibration loop using structural estimating equations derived from the model.

To estimate the sectoral supply elasticity ϱ_2^f, we begin with the model-implied sectoral labor supply expression in equation (10). Taking logs and differencing over time yields the following:

$$\Delta \log \mu_{\ell st}^f = \varrho_2^f \Delta \log w_{\ell st}^f + \Delta \log \left(\sum_{s'} B_{\ell s' t}^f (w_{\ell s' t}^f)^{\varrho_2^f} \right) + \Delta \log B_{\ell st}^f. \tag{13}$$

We directly observe changes in employment shares and wages in the Census data. The term involving the sum can be controlled for using (ℓ, f, t) fixed effects. However, the third term captures changes in unobserved sector and type-specific amenities within each location, which can bias OLS estimates of ϱ_2^f.

To address this endogeneity, we construct a leave-one-out Bartik-style instrument for sectoral wage growth within a location:

$$\text{IV}_{\ell st}^f = \sum_{\ell' \neq \ell} \psi_{\ell' st|-\ell}^f \Delta \log w_{\ell' st}^f,$$

where $\psi^f_{\ell' st|-\ell}$ denotes the share of total (s, f) employment outside of location ℓ accounted for by location ℓ'. The instrument captures the average wage growth among type-f workers in sector s outside of the location ℓ. Our identification assumption is that, conditional on location-type-year fixed effects, the instrument $\text{IV}^f_{\ell st}$ is uncorrelated with changes in sectoral amenities *within* location ℓ.

To increase statistical power, we estimate equation (13) using data from all NAICS 1-digit sectors, rather than aggregating non-Business Services industries into a single residual category. Panel A of Table OA.1 presents the results using 10-year differences from 1980 to 2010 for all 722 commuting zones. Columns 1 and 2 report unweighted estimates, while Columns 3 and 4 include population weights and are our preferred specifications.

The estimated elasticities are higher for college-educated workers than for non-college workers, consistent with greater mobility of high-skill labor. Our estimates fall at the upper end of the range reported by Artuç, Chaudhuri, and McLaren (2010), who estimate pooled elasticities for all types of workers.

To estimate the spatial supply elasticity ϱ^f_1, we take logs of the spatial labor supply equation (10) and difference it over time:

$$\text{(14)} \qquad \Delta \log \lambda^f_{\ell t} = \varrho^f_1 \Delta \log \left(r^{-\alpha^f}_{\ell t} \omega^f_{\ell t} \right) - \Delta \log \sum_{\ell} (r^{-\alpha^f}_{\ell t} \omega^f_{\ell t})^{\varrho^f_1} + \Delta \log \bar{B}^f_{\ell t}.$$

The first term represents a deflated wage index. The second term is absorbed by type-year fixed effects. The third term captures changes in unobserved location amenities, which can bias OLS estimates of ϱ^f_1.

We construct the deflated wage index on the right-hand side of equation (13) using data objects and previous estimates. Specifically, we obtain the residential rental rate, $r_{\ell t}$, and the housing expenditure share, α^f, from Census data.[20] We obtain $\Delta \log \omega^f_{\ell t}$ as a transformation of the (ℓ, f, t) fixed effects from the regression in equation (13).

To identify the spatial elasticity of labor supply, ϱ^f_1, we construct a Bartik-style instrument based on initial sectoral employment shares:

$$\text{IV}^f_{\ell t} = \sum_s \mu^f_{\ell st} \Delta \log w^f_{st|-\ell},$$

where $\mu^f_{\ell st}$ is the initial share of type-f workers in sector s in location ℓ, and $\Delta \log w^f_{st|-\ell}$

[20]We estimate rental rates by running hedonic regressions of log residential rent expenditures on a rich set of housing characteristics, using the resulting CZ-year fixed effects as our index of local rental rates. To obtain housing expenditure shares, we compute average rental payments as a share of income for college- and non-college-educated workers in the Census. This yields housing expenditure shares of $\alpha^f = 0.18$ for college workers and $\alpha^f = 0.32$ for non-college workers.

is the wage growth for type-f workers in sector s outside commuting zone ℓ. The exclusion restriction assumes that these initial shares are not correlated with future changes in local amenities. Columns 1 and 2 of Panel B in Table OA.1 report IV estimates based on 10-year differences from 1980 to 2010 across commuting zones. We estimate ϱ_1^f to be 3.4 for non-college workers and 4.8 for college-educated workers.

We assess the robustness of our approach using an alternative specification following Diamond (2016), which includes changes in the wage index and residential rents separately and instruments for each. The wage index continues to be instrumented with $\text{IV}_{\ell t}^f$, while rent changes are instrumented by interacting $\text{IV}_{\ell t}^f$ with the Wharton Land Use Regulation Index (Saiz, 2010; Gyourko et al., 2013). Columns 3 and 4 of the same table present results from this alternative specification. The resulting elasticity estimates remain similar to those from the baseline and align closely with the estimates in Diamond (2016), supporting the robustness of our exclusion restriction and the reliability of our identification strategy.

Other Structural Parameters. We calibrate the tail parameter of the firm productivity distribution, ν_s, to match the empirical tail of the establishment size distribution in the LBD, producing values of 6.49 for Business Services and 2.89 for the other sector. The capitalist's discount factor, β, is set to 0.97 to match a long-run interest rate of 3%. The firm exit rate, $\xi = 0.1$, approximates the average observed exit rate in the LBD during our sample period. Depreciation rates for IT capital are taken directly from the BEA Fixed Asset Tables. Finally, we set the substitution elasticity across sectoral varieties ι_s, to 4, consistent with previous structural work using the LBD (Garcia-Macia, Hsieh, and Klenow, 2019; Peters and Walsh, 2024).[21] For simplicity, we assume the same elasticity of substitution within and between sectors.

Productivities, Amenities, and Land Supply. Given the estimated structural parameters, we invert the model's equilibrium conditions to recover the location-, sector-, type-, and time-specific productivities ($A_{\ell st}^f$) and amenities ($\bar{B}_{\ell t}^f$, $B_{\ell st}^f$) that rationalize the observed distribution of wages and employment across commuting zones, sectors, education groups, and years. Following Redding and Rossi-Hansberg (2017), this inversion yields a unique set of structural residuals for any parameter vector, ensuring that the model exactly reproduces the data along the entire transition path. Starting in 2015, we hold all productivity and amenity residuals fixed and simulate the model forward until it converges to a steady state.

Averaging across skill groups within each location and sector, we find that labor productivity is positively correlated with population density in the cross-section of locations consistent with our mechanism (cf. bullet (iii), Proposition 1). This correlation is espe-

[21] Hottman, Redding, and Weinstein (2016) report similar demand elasticities for US consumer goods.

cially strong in Business Services and weaker in the residual sector, suggesting that our mechanism is particularly strong in Business Services. These correlations reflect the fact that amenity and productivity residuals are themselves strongly correlated: the same locations tend to exhibit both high productivity and high residential attractiveness.[22]

None of the productivity or amenity residuals exhibit urban-biased growth between 1980 and 2015. This indicates that changes in these residuals are not a major source of urban-biased wage growth. We confirm this conclusion formally in the general equilibrium counterfactuals presented below.

In addition to productivity and amenities, we recover several other parameters as structural residuals. The IT capital transformation rate, $\mathcal{Z}_t$, is chosen to match the BEA's IT capital price index for each year. Sectoral IT productivities, A_s^K, are disciplined using the ratio of IT capital stock to total payroll in each sector in 1980, where IT capital stocks are sourced from the BEA Fixed Asset Tables (cf. Figure 7). We infer the supply of residential housing, $\bar{X}_{\ell t}^R$, to match observed commuting zone rent indices in each year. Given the lack of data on commercial rents, we assume that the supply of commercial land is proportional to the supply of residential housing. We normalize the proportionality constant to 1, as it is not separately identified from the sectoral entry cost shifters τ_s.

This inversion-based approach is a central strength of our analysis. All unmodeled forces, such as changes in non-IT capital, shifts in other factor prices, or institutional variation, are absorbed by the structural residuals. The model attributes urban-biased wage growth to falling IT prices only when this is justified by the estimated elasticities. Any remaining variation in the data is captured by the residuals. If the mechanism has no explanatory power, the residuals account for the full extent of urban-biased growth. In this sense, the quantitative results below serve as a direct test of the mechanism's ability to explain the observed patterns.

3.2 Location-Sector Exposure in the Calibrated Model

A central feature of the calibrated model is that the capital-labor ratio increases with firm scale within each location-sector. The left panel of Figure 9 illustrates this relationship across firms in several representative commuting zones, with firm size measured by employment. Driving these patterns in the model are the negative estimated values of $\bar{\epsilon}_s$, which imply a complementarity between capital and firm scale in both sectors.

Figure 9 shows that capital–labor ratios differ across cities even among firms with the same employment size. These differences reflect spatial variation in labor productivity: in more productive locations, firms of a given size produce more output and thus

[22]Figure OA.19 in the Online Appendix graphs all the recovered productivity residuals against population density; Figure OA.17 shows the same for amenities.

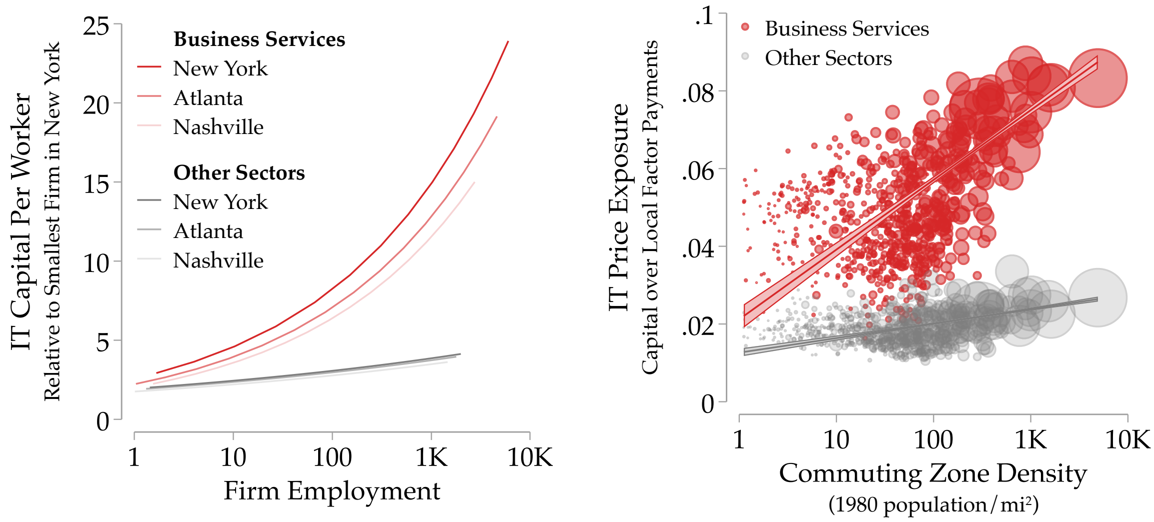
TABLE 2: OVERVIEW OF MODEL PARAMETERIZATION

	Estimated Structural Parameters	*Value*	*Description of Moment*	*Moment: Model/Data*
$\bar{\epsilon}_s$	Non-homotheticity	(-0.18, -0.07)	2002-2015 Elasticity of IT capital per worker to firm sales	(0.22, 0.13)/ (0.22, 0.13)
φ_s	EoS College- and Non-college Labor	(1.24, 1.57)	1992 Elasticity of college share to firm size	(0.05, 0.09)/(0.05, 0.09)
σ	EoS College Labor and IT Capital	0.55	2007 Macro-elasticity from Lashkari et al. (2024)	0.95/0.95
τ_s	Entry-Cost Shifter	(651, 6866)	1980 Average establishment size by sector	(11.7, 14.4)/(11.7, 14.4)
η_s	Land Share in Entry Cost	(0.18, 0.14)	1980 Elasticity of estab. size to pop. density	(0.17, 0.10)/(0.17, 0.10)
ϱ_1^f	Spatial Labor-Supply Elasticity	(3.5, 4.8)	Estimated using equation (14)	N/A
ϱ_2^f	Sectoral Labor-Supply Elasticity	(0.57, 1.11)	Estimated using equation (13)	N/A
α^f	Housing Share in Final Consumption	(0.32, 0.18)	1980–2015 Avg. rent payments over income	(0.32, 0.18)/(0.32, 0.18)
ν_s	Pareto Shape Parameter	(6.49,2.98)	Tail parameter of LBD estab. size dist.	(1.1)/(1.1)
ξ	Firm Exit Rate	0.1	1980 LBD Exit Rate	(10%)/(10%)
	External Structural Parameters	*Value*	*Source*	*Moment: Model/Data*
ι_s	Sectoral Demand Elasticity	(4, 4)	Garcia-Macia et al. (2019)	N/A
γ	Sectoral Elasticity of Substitution	∞	N/A	N/A
β	Capitalist Discount Rate	0.97	Long-run interest rate of 3%	N/A
	Productivities, Amenities, and Land	*Value*	*Data Matched*	*Moment: Model/Data*
$A_{\ell st}^f$	Location Productivity Shifter	Various	1980–2015 CZ-sector-education-specific wages and employment	Various
A_{st}^K	Sectoral IT Capital Productivity	Various	1980 IT capital stock over total payroll by sector	Various
$B_{\ell st}^f$	Sectoral Amenities	Various	1980–2015 CZ-sector-education-specific wages and employment	Various
$\bar{B}_{\ell t}^f$	Location Amenities	Various	1980–2015 CZ-sector-education-specific wages and employment	Various
$\bar{X}_{\ell t}^R$	Residential Housing Supply	Various	1980–2015 CZ-specific residential rent indices	Various
$\bar{X}_{\ell st}^C$	Commercially-zoned Land Supply	Various	Proportional to residential housing supply	Various
$\mathcal{Z}_t$	Productivity of IT Production	Various	1980–2015 BEA IT Capital Price Index	Various
δ_t	IT Capital Depreciation Rate	Various	BEA Fixed Asset Tables	Various

Notes: This table shows the baseline parameterization of the model. The values of productivity, amenity, and land supply terms vary across locations, sectors, and factor types, and are therefore not listed. Where two values appear for a sector-specific parameter, the value for Business Services is listed first. Where two values appear for an education-group-specific parameter, the value for non-college workers appears first.

FIGURE 9: IT CAPITAL PER WORKER AND IT PRICE EXPOSURE IN THE MODEL

(A) IT Capital Per Worker, 1980 (B) IT Capital Price Exposure, 1980



Notes: The figure reports model outcomes for 1980. The left panel shows policy functions mapping firm size to optimal capital per worker across representative locations, separately by sector. Capital per worker is normalized to 1 for a one-employee Business Services firm in New York. The right panel displays the exposure statistic to IT price changes for each location-sector pair, as defined in equation (12). This statistic equals the present-discounted value of capital payments relative to payments to local factors at the average entering firm in that location-sector.

operate at a larger scale, y. Because the production function is non-homothetic, larger scale implies higher capital intensity. As output differences widen with firm size, the capital–labor ratio gap across cities increases. The model therefore replicates the empirical finding that urban-biased wage growth is most pronounced among large employers (see Figure OA.9 in the Online Appendix).

The left panel of Figure 9 also shows that our model captures two empirical patterns documented in distinct strands of the literature. First, larger and more productive firms have lower labor shares (e.g., Autor, Dorn, Katz, Patterson, and Van Reenen, 2020) and higher IT intensity (Lashkari et al., 2024). Second, labor shares decline with city size (Lindenlaub, Oh, and Peters, 2024), and urban firms exhibit higher IT intensity (Eeckhout et al., 2021; Beaudry, Doms, and Lewis, 2010).[23] In our model, these patterns emerge jointly as equilibrium outcomes.

Differences in capital–labor ratios across firms and locations, together with the larger average firm size in high-density areas, generate equilibrium variation in exposure to IT price changes across location–sectors. We compute the theory-consistent exposure terms from Theorem 1 for each sector in the calibrated model and plot them against population

[23]Relatedly, Rubinton (2025) shows that IT *investments* per worker rise with city size. We emphasize that IT stocks and investments are distinct: investments can differ markedly from stocks because larger firms are far more likely to invest in IT in any given year (see Jiang and Rubinton, 2024; Lashkari et al., 2024). We deepen this discussion in Section B.5 of the Online Appendix.

density in the right panel of Figure 9. The resulting patterns closely mirror the empirical geography of urban-biased growth: exposure rises sharply with population density in Business Services but is relatively flat in other sectors.

We provide intuition for both the level and slope differences in exposure across sectors shown in the right panel of Figure 9. First, level differences reflect variation in the productivity of IT capital, A_s^K, which we calibrate separately for each sector to match the 1980 ratio of IT capital to total payroll. In that year, Business Services used more than three times as much IT capital per dollar of payroll as other sectors. The calibration captures this fact through a higher value for A_s^K, generating a stronger average exposure in Business Services across all locations.

Second, the degree to which exposure increases with density varies dramatically across sectors. The steep gradient in Business Services arises from the interaction of the scale and neoclassical channels introduced in Section 2.1. The scale channel is particularly strong in Business Services for three reasons: (i) $\bar{\epsilon}_s$ is more negative, steepening the relationship between firm size and capital intensity; (ii) η_s is higher, making average firm size increase more sharply with density; and (iii) the correlation between labor productivity and density is stronger in the cross-section of locations. While the neoclassical channel also contributes, it is dominated by the scale channel—especially in Business Services.

In sum, the calibrated exposure patterns in Figure 9 suggest that the observed decline in IT prices can generate urban-biased wage growth consistent with the empirical facts documented in Section 1. We now turn to a general equilibrium counterfactual to evaluate this implication quantitatively.

4. Accounting for Urban-Biased Growth

How much of the urban-biased wage growth observed in the data can be attributed to the observed decline in the investment price of IT capital? We answer this question by using the calibrated model for a growth accounting exercise.

Main Counterfactual. Our main "IT-only" counterfactual isolates the effect of declining IT capital prices. We hold all structural residuals—location- and sector-specific productivities, amenities, and land supplies—fixed at their 1980 levels. We then solve the model forward, varying only the productivity of the IT-capital-producing sector, $\mathcal{Z}_t$. As $\mathcal{Z}_t$ increases from its 1980 to 2015 value, the model replicates the observed decline in the investment price of IT capital. To avoid confounding composition effects, we also let the *aggregate* supply of college and non-college labor evolve as in the data. This

TABLE 3: WAGE-DENSITY GRADIENTS IN DATA AND MODEL

	Data		IT-only Economy 2015			
	1980	2015	Base	$\bar{\epsilon}_s = 0$	Endog. $A^f_{\ell st}$	Endog. $\bar{B}^f_{\ell t}$
Business Services	0.070	0.154	0.137	0.077	0.137	0.136
Other Sectors	0.060	0.070	0.071	0.064	0.071	0.070
Aggregate	0.063	0.102	0.093	0.070	0.093	0.091
Δ Aggregate		0.039	0.030	0.007	0.030	0.028

Notes: This table reports the coefficient on log population density from regressions of log average wages on population density across US commuting zones, in the data and in simulated economies ("IT-only" economy). The 1980 cross-section is identical in the data and the IT-only model by construction. Data columns use the 1980 Decennial Census and 2015 American Community Survey. Column 3 shows results from the baseline IT-only counterfactual. Column 4 imposes homothetic production ($\bar{\epsilon}_s = 0$) while keeping structural parameters fixed and re-calibrating regional fundamentals. Column 5 allows local productivity to rise with population density. Column 6 lets local amenities for college workers increase with the local college employment share.

ensures that local college shares remain comparable across model and data.[24]

We find that falling IT prices alone explain most of the urban-biased wage growth observed in the data, as measured by the steepening of the wage-density gradient.[25] In the IT-only economy, the elasticity of wages with respect to density increases from 0.063 to 0.093, compared to 0.102 in the data.[26] This accounts for 77% of the observed increase between 1980 and 2015. Table 3 reports these estimates in the "base" column.

Table 3 also shows that the IT price decline generates urban-biased growth in Business Services and not in other sectors, matching the fact that urban-biased growth is a Business Services specific phenomenon. The model predicts this sectoral dimension of IT-price-induced urban-biased growth because of the sectoral difference in exposure shown in the right panel of Figure 9: the exposure of Business Services to IT price declines exhibits a striking gradient with population density, which is substantially weaker in the residual sector.

Figure 10 visualizes the same results as Table 3, but shows the full distribution of wage growth across commuting zone density deciles. The model closely replicates the urban-biased growth observed in the data, though it slightly underpredicts wage growth in the most densely populated commuting zones.

The IT-only economy closely replicates the division between wage and employment

[24] We verify in Online Appendix B.4 that the aggregate rise in the relative supply of college workers does not, by itself, generate any urban-biased growth.

[25] Declining IT prices explain most of the spatial divergence in wage growth, but not the overall rise in average wages. Matching aggregate wage growth from 1980 to 2015 requires broad-based productivity gains across all locations.

[26] Because the model is calibrated to match the 1980 cross-section, it replicates the wage-density gradient in that year exactly.

responses observed in the data. Figure 11 implements the decompositions of Figure 4 in the model-generated data and contrasts them with their counterparts in the data.[27] While the model slightly understates the total contribution of Business Services to urban-biased growth, it closely replicates its composition: in the data, 81% of the sector's contribution reflects wage growth differentials, compared to 83% in the IT-only counterfactual.

Falling IT prices also shift the composition of the Business Services workforce toward more educated workers, especially in high-density cities, consistent with the patterns observed in the data. Although the aggregate share of college-educated workers matches the data in all years by construction, the sorting of workers across locations, sectors, and firms in the IT-only economy is entirely endogenous. Figure OA.20 in the Online Appendix shows that the model reproduces the observed increase in college share within Business Services over time. It slightly understates the shift in the densest cities, but captures the broader trend well.

The model also attributes most of the urban-biased growth to large firms, in line with the data. We replicate the decomposition by establishment size from Figure 5 using the model output, shown in Figure OA.18 in the Online Appendix. The IT-only economy somewhat overstates the role of large firms because, by construction, all firms within a given location-sector pay the same wage. In contrast, larger firms in the data pay higher wages to similar workers (Trottner, 2022), consistent with upward-sloping labor supply curves that limit firm growth. Incorporating firm-specific labor supply elasticities could improve the fit of the model in this particular dimension.

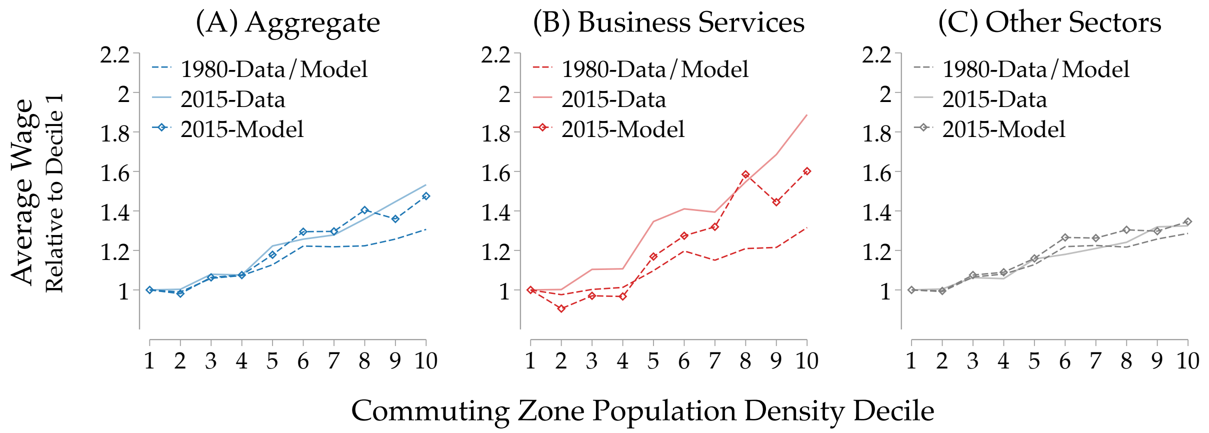
Additional Counterfactuals and Robustness Exercises. We present a set of additional counterfactuals that clarify how the mechanism operates and confirm the robustness of our results.

To illustrate the central role of the non-homotheticity parameter governing the complementarity between capital and firm scale in variable costs, we set $\bar{\epsilon}_s = 0$ and re-calibrate all structural residuals to match the same panel targets as in our baseline. When we repeat the IT-only counterfactual under this restriction, the model generates substantially less urban-biased growth, as shown in Column 4 of Table 3.

Even when $\bar{\epsilon}_s = 0$, the IT-only economy generates some urban-biased growth, indicating that exposure to IT price declines remains elevated in high-density locations. This residual exposure arises because larger firms operate at higher capital intensity than smaller firms whose cost structures rely more heavily on entry costs that do not use capital. As a result, the scale channel remains active even in the homothetic cost function case. Column 4 of Table 3 shows, however, that this mechanism plays a modest

[27] For direct comparability, we use the US Decennial Census data—also used in the model's calibration—rather than the LBD, leading to minor differences relative to the decompositions in Figure 4 in Section 1.

FIGURE 10: URBAN-BIASED GROWTH IN MODEL AND DATA



Notes: This figure shows average annual wages across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density in the model and the data. Each decile accounts for one-tenth of the US population in 1980. The 1980 data come from the US Decennial Census, and the 2015 data from the American Community Survey. The model data comes from a counterfactual economy in which only the investment price of IT and the aggregate share of college workers change, as in the data. The 1980 data and model are identical by construction.

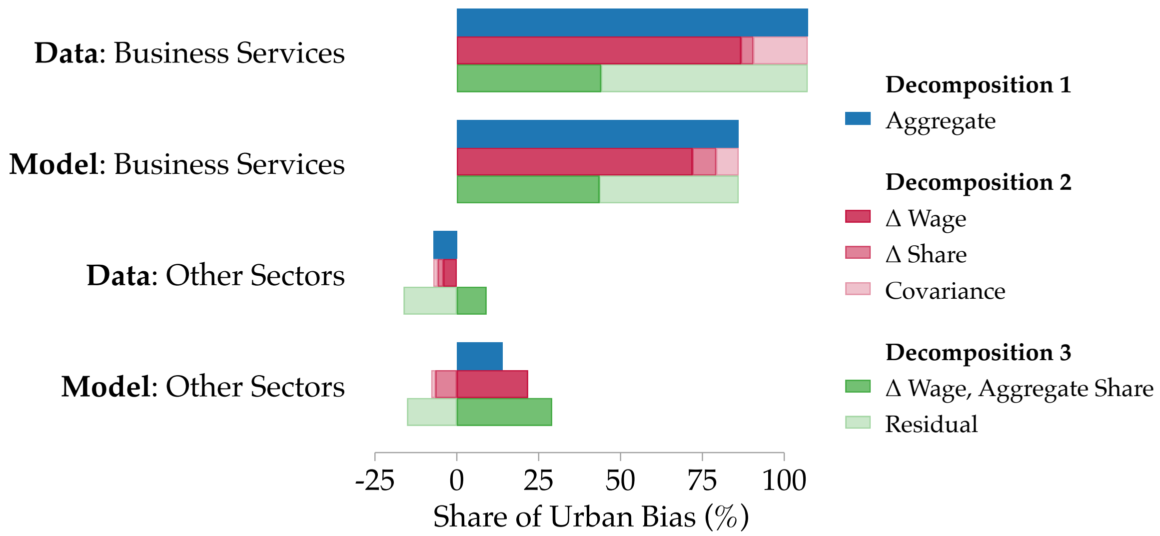
role: the non-homotheticity in variable cost accounts for the bulk of the urban-biased exposure to falling IT prices.

Our baseline theory treats local productivity and amenities as exogenous, even though agglomeration forces are central to the spatial literature. To test the robustness of our results, we allow productivity and amenities to depend on local conditions. First, we let productivity increase with population density, using the elasticity estimates from Ahlfeldt and Pietrostefani (2019). Column 5 of Table 3 shows that this change has little effect on the role of declining IT prices in shaping the wage-density gradient. The reason is that the spatial reallocation induced by urban-biased growth is too small to meaningfully affect population density. Second, using estimates from Diamond (2016), we allow the amenities of college workers to increase with the college share in local employment. Column 6 shows that this slightly lowers wage growth in dense areas, consistent with higher amenities reducing wages in spatial equilibrium.

An important input in our calibration is the elasticity of IT capital per worker to firm size estimated in Table 1. As a cross-validation, we use alternative estimates of this elasticity from Lashkari et al. (2024), who document the same relationship using French firm-level data. We recalibrate $\bar{\epsilon}_s$ to target their empirical elasticity instead.[28] Table OA.2 shows that this alternative calibration slightly amplifies the urban-biased wage growth generated by the IT price decline. This reflects the stronger positive

[28] Lashkari et al. (2024) do not report estimates of the scale elasticity separately for each sector. As a result, we target the within-firm relationship between firm size and capital intensity reported in their paper while preserving the cross-sectoral differences in coefficients from Table 1. Lashkari et al. (2024) also report a "causal" elasticity obtained via an instrumental variable strategy; reassuringly, this elasticity is similar to the "correlational" elasticity obtained from their within-firm regressions.

FIGURE 11: DECOMPOSING URBAN-BIASED GROWTH IN MODEL AND DATA



Notes: The figure decomposes the difference in 1980–2015 wage growth between commuting zones with above-median and below-median densities in 1980 into the contributions of each NAICS 1-digit sector, separately in data and model output.

relationship between capital intensity and firm scale found by Lashkari et al. (2024) in French data compared to our estimates for the US economy.

Our findings are also sensitive to the aggregate elasticity of substitution between capital and labor, which affects how exposure to IT price changes varies across locations and sectors (see equation 7). Our baseline calibration targets an elasticity of 0.95 from Lashkari et al. (2024), specific to IT capital, in contrast to broader estimates that apply to aggregate equipment capital. A lower elasticity of 0.65 from Oberfield and Raval (2021) weakens the mechanism, while a higher value of 1.25 from Karabarbounis and Neiman (2014) amplifies it. Table OA.2 in the Online Appendix reports the corresponding results.

Table OA.2 reports several additional robustness checks. Columns 3 and 4 allow productivity and amenity residuals to vary as calibrated, while instead holding the price of IT capital fixed at its 1980 level. The resulting wage-density gradient remains flat, confirming that these structural residuals alone do not generate urban-biased growth. Columns 7 to 9 repeat the main IT-only counterfactual while varying additional model parameters. Column 7 uses a common labor supply elasticity across education groups instead of separate estimates. Column 8 replaces our estimated substitution elasticity between capital and labor with the value of Krusell et al. (2000). Column 9 holds aggregate college shares fixed at their 1980 levels instead of allowing them to vary as in the data. In all three cases, IT-induced changes in the wage-density gradient remain nearly identical to those in our baseline IT-only counterfactual.

CONCLUSION

This paper shows that the decline in IT prices generated wage growth that was not only skill-biased, as emphasized by Autor, Levy, and Murnane (2003), but also urban-biased, favoring cities with high population density. Most of the rise in the wage-density gradient since 1980 can be accounted for by falling IT prices interacting with spatial and sectoral variation in IT intensity.

Our model provides a transparent and testable account of this transformation, disciplined by two empirical facts: firm size increases with population density, and larger firms use more IT capital per worker. The mechanism does not rely on changes in unobserved local amenities or productivities. It follows directly from firm optimization. As IT prices fall, firms that use IT intensively benefit from greater cost savings, leading to higher productivity and increased labor demand.

Because large Business Services firms in high-density locations are the most IT-intensive, they contribute disproportionately to urban-biased wage growth. Our findings highlight that the spatial consequences of technological change depend not only on regional sectoral specialization, but also on differences in the input usage of firms across space.

REFERENCES

AHLFELDT, G. M. AND E. PIETROSTEFANI (2019): "The Economic Effects of Density: A Synthesis," *Journal of Urban Economics*, 111, 93–107.

ALLEN, T. AND C. ARKOLAKIS (2014): "Trade and the Topography of the Spatial Economy," *The Quarterly Journal of Economics*, 129, 1085–1140.

ALMAGRO, M. AND T. DOMÍNGUEZ-IINO (2025): "Location sorting and endogenous amenities: Evidence from amsterdam," *Econometrica*, 93, 1031–1071.

ARTUÇ, E., S. CHAUDHURI, AND J. MCLAREN (2010): "Trade Shocks and Labor Adjustment: A Structural Empirical Approach," *American Economic Review*, 100, 1008–45.

AUTOR, D. (2019): "Work of the Past, Work of the Future," in *AEA Papers and Proceedings*, vol. 109, 1–32.

AUTOR, D. AND D. DORN (2013): "The Growth of Low-skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103, 1553–97.

AUTOR, D., D. DORN, L. F. KATZ, C. PATTERSON, AND J. VAN REENEN (2020): "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly journal of economics*, 135, 645–709.

AUTOR, D., F. LEVY, AND R. J. MURNANE (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118, 1279–1333.

BAUM-SNOW, N. AND R. PAVAN (2013): "Inequality and City Size," *Review of Economics and Statistics*, 95, 1535–1548.

BEAUDRY, P., M. DOMS, AND E. LEWIS (2010): "Should the Personal Computer be Considered a Technological Revolution? Evidence from US Metropolitan Areas,"

Journal of Political Economy, 118, 988–1036.
BERRY, C. R. AND E. L. GLAESER (2005): "The Divergence of Human Capital Levels Across Cities," *Papers in Regional Science*, 84, 407–444.
BILAL, A. AND E. ROSSI-HANSBERG (2023): "Anticipating Climate Change Across the United States," Tech. rep., National Bureau of Economic Research.
COMBES, P.-P., G. DURANTON, L. GOBILLON, D. PUGA, AND S. ROUX (2012): "The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection," *Econometrica*, 80, 2543–2594.
COUTURE, V. AND J. HANDBURY (2020): "Urban Revival in America," *Journal of Urban Economics*, 119.
DAVIS, D. R. AND J. I. DINGEL (2020): "The Comparative Advantage of Cities," *Journal of International Economics*, 123, 103291.
DESMET, K., D. K. NAGY, AND E. ROSSI-HANSBERG (2018): "The Geography of Development," *Journal of Political Economy*, 126, 903–983.
DESMET, K. AND E. ROSSI-HANSBERG (2014): "Spatial Development," *American Economic Review*, 104, 1211–1243.
DIAMOND, R. (2016): "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 106, 479–524.
ECKERT, F. (2019): "Growing Apart: Tradable Services and the Fragmentation of the US," *Working Paper*.
EECKHOUT, J., C. HEDTRICH, AND R. PINHEIRO (2021): "IT and Urban Polarization," *CEPR Discussion Paper No. DP16540*.
EHRLICH, M. V. AND H. G. OVERMAN (2020): "Place-based Policies and Spatial Disparities across European Cities," *Journal of Economic Perspectives*, 34, 128–49.
FOGLI, A., V. GUERRIERI, M. PONDER, AND M. PRATO (2023): "The End of the American Dream? Inequality and Segregation in US Cities," Tech. rep., National Bureau of Economic Research.
FORT, T. C. AND S. D. KLIMEK (2016): "The Effects of Industry Classification Changes on US Employment Composition," *Tuck School at Dartmouth mimeo*.
GANAPATI, S. (2025): "The Modern Wholesaler: Global Sourcing, Domestic Distribution, and Scale Economies," *American Economic Journal: Microeconomics*, 17, 1–40.
GANONG, P. AND D. SHOAG (2017): "Why has Regional Income Convergence in the US Declined?" *Journal of Urban Economics*, 102, 76–90.
GARCIA-MACIA, D., C.-T. HSIEH, AND P. J. KLENOW (2019): "How Destructive is Innovation?" *Econometrica*, 87, 1507–1541.
GIANNONE, E. (2022): "Skilled-biased Technical Change and Regional Convergence," *Working Paper*.
GLAESER, E. L. AND A. SALZ (2004): "The Rise of the Skilled City." *Brookings-Wharton Papers on Urban Affairs*.
GYOURKO, J., C. MAYER, AND T. SINAI (2013): "Superstar Cities," *American Economic Journal: Economic Policy*, 5, 167–99.
HOTTMAN, C. J., S. J. REDDING, AND D. E. WEINSTEIN (2016): "Quantifying the Sources of Firm Heterogeneity," *The Quarterly Journal of Economics*, 131, 1291–1364.
JAIMOVICH, N. AND H. E. SIU (2020): "Job Polarization and Jobless Recoveries," *Review of Economics and Statistics*, 102, 129–147.
JIANG, X. (2023): "Information and Communication Technology and Firm Geographic Expansion," *mimeo*.

JIANG, X. AND H. RUBINTON (2024): "The Adoption of Non-Rival Inputs and Firm Scope," *CESifo Working Paper*.

KARABARBOUNIS, L. AND B. NEIMAN (2014): "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 129, 61–103.

KLEINMAN, B. (2022): "Wage Inequality and the Spatial Expansion of Firms," Tech. rep., mimeo.

KLEINMAN, B., E. LIU, AND S. J. REDDING (2023): "Dynamic Spatial General Equilibrium," *Econometrica*, 91, 385–424.

KLENOW, P. J. AND H. LI (2025): "Entry Costs Rise with Growth," *Journal of Political Economy Macroeconomics*, 3, 43–74.

KRUEGER, A. B. (1993): "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989," *The Quarterly Journal of Economics*, 108, 33–60.

KRUSELL, P., L. E. OHANIAN, J.-V. RÍOS-RULL, AND G. L. VIOLANTE (2000): "Capital-skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68, 1029–1053.

LASHKARI, D., A. BAUER, AND J. BOUSSARD (2024): "Information Technology and Returns to Scale," *American Economic Review*, 114, 1769–1815.

LINDENLAUB, I., R. OH, AND M. PETERS (2024): "Spatial Firm Sorting and Local Monopsony Power," *Working Paper*.

MARTELLINI, P. (2022): "Local Labor Markets and Aggregate Productivity," Tech. rep., Working paper.

MORETTI, E. (2012): *The New Geography of Jobs*, Houghton Mifflin Harcourt.

NAGY, D. K. (2023): "Hinterlands, City Formation and Growth: Evidence from the US Westward Expansion," *Review of Economic Studies*, 90, 3238–3281.

OBERFIELD, E. AND D. RAVAL (2021): "Micro Data and Macro Technology," *Econometrica*, 89, 703–732.

PETERS, M. AND C. WALSH (2024): "Population Growth and Firm Dynamics," Tech. rep., National Bureau of Economic Research.

REDDING, S. J. (2016): "Goods Trade, Factor Mobility and Welfare," *Journal of International Economics*, 101.

REDDING, S. J. AND E. ROSSI-HANSBERG (2017): "Quantitative Spatial Economics," *Annual Review of Economics*, 9, 21–58.

ROSSI-HANSBERG, E., P.-D. SARTE, AND F. SCHWARTZMAN (2025): "Cognitive Hubs and Spatial Redistribution," Tech. rep., National Bureau of Economic Research.

RUBINTON, H. (2025): "The Geography of Business Dynamism and Skill-Biased Technical Change," *Review of Economic Studies*.

RUGGLES, S., K. GENADEK, R. GOEKEN, J. GROVER, AND M. SOBEK (2017): "Integrated Public Use Microdata Series: Version 7.0," *Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D010.V7.0*.

SAIZ, A. (2010): "The Geographic Determinants of Housing Supply," *The Quarterly Journal of Economics*, 125, 1253–1296.

SATO, R. (1977): "Homothetic and Non-homothetic CES Production Functions," *The American Economic Review*, 67, 559–569.

SCALA, D. J. AND K. M. JOHNSON (2017): "Political Polarization Along the Rural-urban Continuum? The Geography of the Presidential Vote," *Annals of the American Academy of Political and Social Science*, 672.

TOLBERT, C. M. AND M. SIZER (1996): "US Commuting Zones and Labor Market Areas: A 1990 Update," Tech. rep., United States Department of Agriculture, Economic

Research Service.
TROTTNER, F. (2022): "Who Gains from Scale?" *Working Paper*.
WALSH, C. (2025): "The Entry Multiplier," *mimeo*.

Online Appendix

Urban-Biased Growth: A Macroeconomic Analysis

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FOR ONLINE PUBLICATION

A. Proofs and Derivations

In this section, we derive the main theoretical results of the paper.

A.1 Derivations for Section 2.1: Capital-Scale Complementarities and Urban-Biased Growth

In this section, we derive all the results for Section 2.1 entitled "Capital-Scale Complementarities and Urban-Biased Growth."

A.1.1 Derivation of the Demand System

Index the differentiated varieties produced by intermediate input firms in the economy by v. Denote the total number of varieties in each sector by N_s. The representative firm produces the final good using the following technology:

$$Y = \left(\sum_s \left(\int_0^{N_s} q_s^{\zeta_s}(v)dv \right)^{\frac{\varsigma}{\zeta_s}} \right)^{\frac{1}{\varsigma}} := \left(\sum_s Q_s^{\varsigma} \right)^{\frac{1}{\varsigma}},$$

where $q_s(v)$ denotes the quantity of differentiated variety v used by the representative firm, the substitution elasticity over firm varieties within a sector is $\iota_s := \frac{1}{1-\zeta_s}$, and the elasticity of substitution over sectoral CES bundles, Q_s, is $\gamma := \frac{1}{1-\varsigma}$.

Solving the representative firm's profit maximization problem yields the standard demand curve for any individual variety v:

$$p_s(v) = q_s(v)^{-\frac{1}{\iota_s}} \mathcal{Q}_s \quad \text{where} \quad \mathcal{Q}_s := \frac{P_s^{\frac{\iota_s - \gamma}{\iota_s}}}{P^{\frac{-\gamma}{\iota_s}}} I^{\frac{1}{\iota_s}},$$

and I denotes the total demand for the final good. The optimal sectoral price index, P_s, is defined by $P_s^{1-\iota_s} = \int_0^{N_s} p_s(v)^{1-\iota_s} dv$ and the ideal price index of the final good, P, is defined as $P^{1-\gamma} = \sum_s P_s^{1-\gamma}$. The term $\mathcal{Q}_s$ measures aggregate sector-specific demand. Using the preceding expression, we can then express a firm's revenue function in terms of its own output y(v) and sector-specific aggregate demand:

$$r_s(v) := y(v)^{\zeta_s} \mathcal{Q}_s. \quad \text{(OA.1)}$$

Note that the revenue function for firms is the same across locations since we assume free trade for all goods and services in the economy.

A.1.2 Variation of Wages in the Cross-section

Consider the free entry condition:

$$\max_y \{ Q_s y^{\zeta_s} - C(w_{\ell s}, R, y; A_{\ell s}) \} = 0,$$

where the firm's total cost function (including entry costs) is given by:

$$C(w_{\ell s}, R, y; A_{\ell s}) = yV(w_{\ell s}/A_{\ell s}, R, y) + E(w_{\ell s}, R),$$

Totally differentiating the free entry equation and using the envelope theorem yields the following:

$$d\log Q_s = \frac{C_w w_{\ell s}}{C} d\log w_{\ell s} + \frac{C_R R}{C} d\log R + \frac{C_A A_{\ell s}}{C} d\log A_{\ell s}.$$

Only wages and productivity vary in the cross-section of locations. Using this and rearranging the equation yields:

$$\text{(OA.2)} \qquad \frac{d\log w_{\ell s}}{d\log A_{\ell s}} = \frac{yV_1 \frac{w_{\ell s}}{A_{\ell s}}}{yV_1 \frac{w_{\ell s}}{A_{\ell s}} + E_1 w_{\ell s}} = 1 - \phi^E_{\ell s}$$

where V_1 and E_1 are the partial derivatives of the variable unit cost and the entry cost function with respect to its first argument. The term $\phi^E_{\ell s}$ denotes the fraction of a firm's total labor that is employed in entry cost instead of variable cost in the location-sector pair (ℓ, s).

A.1.3 Variation of Firm Scale in the Cross-section

The firm's first-order condition for its choice of output given its cost-minimizing input choices is given by:

$$Q_s \zeta_s y^{\zeta_s - 1} = C_y := MC_{\ell s},$$

where $MC_{\ell s}$ is the marginal cost of production in location ℓ and sector s. By totally differentiating the first-order condition in the cross-section of locations, we can solve for how firm scale changes, to a first order, as we move from a less to a more productive location:

$$\begin{aligned} &d\log Q_s + [\zeta_s - 1 - \frac{\partial \log MC_{\ell s}}{\partial \log y}] d\log y \\ &\quad = \frac{\partial \log MC_{\ell s}}{\partial \log w_{\ell s}} d\log w_{\ell s} + \frac{\partial \log MC_{\ell s}}{\partial \log R} d\log R + \frac{\partial \log MC_{\ell s}}{\partial \log A_{\ell s}} d\log A_{\ell s}. \end{aligned}$$

In the cross-section of locations, the aggregate demand shifter and the rental rate of capital do not vary. Using this fact and employing the expression in (OA.2) for how wages change with productivity in the cross-section of locations yields:

$$\frac{d\log y}{d\log A_{\ell s}} = \phi^E_{\ell s}\frac{\frac{\partial \log MC_{\ell s}}{\partial \log w_{\ell s}}}{1-\zeta_s+\frac{\partial \log MC_{\ell s}}{\partial \log y}}.$$

Note that $\frac{\partial \log MC_{\ell s}}{\partial \log w_{\ell s}} \geq 0$ is a regularity condition on the production function: if input prices increase, the marginal costs must (weakly) increase. The second regularity condition we impose is that economies of scale are not too strong, so that $\frac{\partial \log MC_{\ell s}}{\partial \log y} > \zeta_s - 1$. This is a general condition in monopolistic competition firm models: the strength of increasing returns must be limited by the elasticity of demand in order to ensure that firm output is bounded.

Note that, under standard regularity conditions, firm scale increases with local productivity. The strength of this relationship is governed by the share of labor in entry costs, $\phi^E_{\ell s}$. When $\phi^E_{\ell s} = 1$, firm scale is highly responsive to productivity; when $\phi^E_{\ell s} = 0$, firm scale is invariant across space. More generally, the higher the labor share in entry costs, the steeper the cross-sectional relationship between firm size and productivity.

A.1.4 Variation of Exposure in the Cross-section

A theory-consistent exposure statistic is the ratio of payments to capital relative to payments to labor at an individual firm in location ℓ and sector s:

$$\Lambda_{\ell s} = \frac{C_R R}{C_w w_{\ell s}},$$

where C_x denotes the partial derivative of the cost function with respect to variable x.

Totally differentiating the exposure statistic $\Lambda_{\ell s}$ with respect to all variables varying in the cross-section of locations yields:

$$\begin{aligned} d\log\Lambda_{\ell s} =& \frac{C_{Ry}y}{C_R}d\log y + \frac{C_{Rw}w_{\ell s}}{C_R}d\log w_{\ell s} + \frac{C_{RA}A_{\ell s}}{C_R}d\log A_{\ell s} \\ &- \frac{C_{wy}y}{C_w}d\log y - \frac{C_{ww}w_{\ell s}}{C_w}d\log w_{\ell s} - \frac{C_{wA}A_{\ell s}}{C_w}d\log A_{\ell s} - d\log w_{\ell s}, \end{aligned}$$

where C_{xy} denotes the cross-partial of the cost function with respect to x and y.

Then combining terms, using Shephard's Lemma, and re-arranging yields:

$$d\log\Lambda_{\ell s} = \left(\frac{\partial \log K/L}{\partial \log w_{\ell s}/R} - 1\right) d\log w_{\ell s} - \frac{\partial \log K^V/L^V}{\partial \log w_{\ell s}/R} d\log A_{\ell s} + \frac{\partial \log K/L}{\partial \log y} d\log y,$$

where factor quantities bearing the superscript V denote inputs used solely for production, while those without the superscript represent total usage across both production and entry.

Replacing elasticities with their respective symbols and dividing through by the difference in sectoral productivities across locations yields:

$$\frac{d\log \Lambda_{\ell s}}{d\log A_{\ell s}} = (\sigma_{KL} - 1)\frac{d\log w_{\ell s}}{d\log A_{\ell s}} - \sigma^{V}_{KL} + \epsilon_{KL}\frac{d\log y}{d\log A_{\ell s}},$$

which is the result of the main text.

A.1.5 Wage Response to IT Price Changes

Next, we totally differentiate the free entry condition over time—rather than across locations—to obtain:

$$\frac{d\log w_{\ell s}}{d\log R} = -\frac{C_R R}{C_w w_{\ell s}} + \frac{C}{C_w w_{\ell s}}\frac{d\log Q_s}{d\log R} = -\Lambda_{\ell s} + (1+\Lambda_{\ell s})\frac{d\log Q_s}{d\log R},$$

where we used Shephard's Lemma, the fact that $C = C_R R + C_w w_{\ell s}$, and the definition of the exposure statistic $\Lambda_{\ell s}$.

A.2 Derivations for Section 2.2: Quantitative Extension

In this section, we present a proof for a more general version of the theorem in Section 2.2 and also derive the implications of the quantitative model for how factor ratios vary with output.

A.2.1 Proof of Theorem 1

In this section, we prove a general version of Theorem 1 for a version of our economy in which firms operate a technology that gives rise to the following total cost function:

(OA.3) $$C_{\ell s}(z;\mathbf{w}_{\ell s},\mathbf{R},y) = yz^{-1}V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y) + E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R}),$$

where $V_{\ell s}$ and $E_{\ell s}$ are unit variable and entry cost aggregators that can vary arbitrarily between locations and sectors, $\mathbf{w}_{\ell s}$ denotes a vector of location-sector-specific factor prices, and $\mathbf{R}$ denotes a vector of rental rates of different types of capital.

In the main text, we considered a special case of this cost function in which productivity is labor-augmenting, the set of local factors includes only high-skill labor, low-skill labor, and commercially zoned land, and there is a single type of capital.[29] Compared to the baseline, the cost function in equation (OA.3) generalizes to include any number of factors, distinguishing between frictionally adjusting factors—whose prices vary across locations and sectors—and perfectly mobile factors, whose prices are equalized across all location-sector pairs.

[29] Some cross-sectional results in the main text rely on specific assumptions about how location-sector productivity shifters enter the production function.

We retain the demand system for firms' differentiated varieties, so that the free entry condition in each location-sector reads as follows in the steady state of the model:

(OA.4)
$$\kappa \int_z \pi_{\ell s}(z) d\Omega_s(z) := \kappa \int_z \max_y \{\mathcal{Q}_s y^{\zeta_s} - y z^{-1} V_{\ell s}(\mathbf{w}_{\ell s}, \mathbf{R}, y)\} d\Omega_s(z) = E_{\ell s}(\mathbf{w}_{\ell s}, \mathbf{R}),$$

where $\kappa := (1-\beta(1-\xi))^{-1} > 1$ captures the rate of time preference and the probability of exogenous exit. The left-hand side hence captures the expected presented discounted value of lifetime operating profits of a firm before entering and drawing its type.

We index individual factors by f. Let $\mathcal{K}$ denote the set of capital factors and $\mathcal{L}$ the set of local factors. Each capital type $f \in \mathcal{K}$ is produced from the numeraire good, with a factor-specific transformation rate $\mathcal{Z}_t^f$.

We state the following generalized version of Theorem 1 based on the cost functions introduced at the beginning of this section.

Theorem. *Suppose that the economy is in steady state, so that factor prices and production technologies are constant over time. Then, the general equilibrium response of the cost-share-weighted payments to local factors $f \in \mathcal{L}$ at the average firm in a location-sector to a change in the rental rate of type-f capital, R^f, is given by*

$$d \log \bar{w}_{\ell s} = -\frac{\Phi_{\ell s}^f}{\Phi_{\ell s}^{\mathcal{L}}} d \log R^f + (1 + \frac{\Phi_{\ell s}^f}{\Phi_{\ell s}^{\mathcal{L}}}) d \log \mathcal{Q}_s,$$

where $\Phi_{\ell s}^f$ and $\Phi_{\ell s}^{\mathcal{L}}$ denote the present discounted values of lifetime payments to type-f capital and all local factors $f' \in \mathcal{L}$ of the average firm at entry, respectively.

Proof. Consider the free entry condition in steady state:

$$\begin{aligned} E_{\ell s}(\mathbf{w}_{\ell s}, \mathbf{R}) &= \kappa \int \pi_{\ell s}(z) d\Omega_s(z) \\ &= \kappa \int \max_y [\mathcal{Q}_s y^{\zeta_s} - y z^{-1} V_{\ell s}(\mathbf{w}_{\ell s}, \mathbf{R}, y)] d\Omega_s(z). \end{aligned}$$

Now by the envelope theorem, at the profit-maximizing level of output $y(z) = y^\star(z)$ of a firm of type z, the following holds:

$$\frac{\partial \pi_{\ell s}(z)}{\partial w_{\ell s}^f} = -z^{-1} y^\star \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s}, \mathbf{R}, y^\star(z))}{\partial w_{\ell s}^f} \quad \text{and} \quad \frac{\partial \pi_{\ell s}(z)}{\partial R^f} = -z^{-1} y^\star \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s}, \mathbf{R}, y^\star(z))}{\partial R^f}.$$

In addition, we also have
$$\frac{\partial \pi_{\ell s}(z)}{\partial \mathcal{Q}_s} = (y^\star(z))^{\zeta_s}.$$

We totally differentiate the free entry condition with respect to all factor prices and aggregate demand terms to obtain:

$$\text{(OA.5)} \quad \sum_{f\in\mathcal{L}} \frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial w^f_{\ell s}} dw^f_{\ell s} + \sum_{f\in\mathcal{K}} \frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial R^f} dR^f$$
$$= \kappa \int \Big((y^\star(z))^{\zeta_s} \mathcal{Q}_s d\log \mathcal{Q}_s - z^{-1} y^\star(z) \sum_{f\in\mathcal{L}} \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial w^f_{\ell s}} dw^f_{\ell s}$$
$$- z^{-1} y^\star(z) \sum_{f\in\mathcal{K}} \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial R^f} dR^f \Big) d\Omega_s(z).$$

Using Shephard's Lemma, we can write the free entry condition:

$$\text{(OA.6)} \quad \sum_{f\in\mathcal{L}} \frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial w^f_{\ell s}} w^f_{\ell s} + \sum_{f\in\mathcal{K}} \frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial R^f} R^f$$
$$= \kappa \int \Big(((y^\star(z))^{\zeta_s} \mathcal{Q}_s - z^{-1} y^\star(z) \sum_{f\in\mathcal{L}} \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial w^f_{\ell s}} w^f_{\ell s}$$
$$- z^{-1} y^\star(z) \sum_{f\in\mathcal{K}} \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial R^f} R^f \Big) d\Omega_s(z).$$

Using equation (OA.6), we can re-write equation (OA.5):

$$\sum_{f\in\mathcal{L}} \left[\frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial w^f_{\ell s}} w^f_{\ell s} + \kappa \int z^{-1} y^\star(z) \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial w^f_{\ell s}} w^f_{\ell s} d\Omega_s(z) \right] d\log w^f_{\ell s}$$
$$+ \sum_{f\in\mathcal{K}} \left[\frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial R^f} R^f + \kappa \int z^{-1} y^\star(z) \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial R^f} R^f d\Omega_s(z) \right] d\log R^f$$
$$= \sum_{f\in\mathcal{L}} \left[\frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial w^f_{\ell s}} w^f_{\ell s} + \kappa \int z^{-1} y^\star(z) \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial w^f_{\ell s}} w^f_{\ell s} d\Omega_s(z) \right] d\log \mathcal{Q}_s$$
$$\text{(OA.7)} \quad + \sum_{f\in\mathcal{K}} \left[\frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial R^f} R^f + \kappa \int z^{-1} y^\star(z) \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial R^f} R^f d\Omega_s(z) \right] d\log \mathcal{Q}_s$$

Now we define the following term for local factor $f \in \mathcal{L}$:

$$\Phi^f_{\ell s} := \frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial w^f_{\ell s}} w^f_{\ell s} + \kappa \int z^{-1} y^\star(z) \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial w^f_{\ell s}} w^f_{\ell s} d\Omega_s(z) \quad \forall f \in \mathcal{L}$$

and similarly for all $f \in \mathcal{K}$:

$$\Phi^f_{\ell s} := \frac{\partial E_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R})}{\partial R^f} R^f + \kappa \int z^{-1} y^\star(z) \frac{\partial V_{\ell s}(\mathbf{w}_{\ell s},\mathbf{R},y^\star(z))}{\partial R^f} R^f d\Omega_s(z) \quad \forall f \in \mathcal{K}.$$

The term $\Phi^f_{\ell s}$ is the present-discounted value of lifetime payments to factor f of the average firm at entry. Using this notation, we can write equation OA.7 as follows:

$$\sum_{f\in\mathcal{L}}\Phi^f_{\ell s}d\log w^f_{\ell s}+\sum_{f\in\mathcal{K}}\Phi^f_{\ell s}d\log R^f=\sum_{f\in\mathcal{L}\cup\mathcal{K}}\Phi^f_{\ell s}d\log\mathcal{Q}_s$$

Now suppose the rental rate of only a single capital input f changes exogenously. In this case we can write the preceding equation as:

$$d\log\bar{w}_{\ell s}=-\frac{\Phi^f_{\ell s}}{\Phi^L_{\ell s}}d\log R^f+(1+\frac{\Phi^f_{\ell s}}{\Phi^L_{\ell s}})d\log\mathcal{Q}_s,$$

where $\Phi^L_{\ell s}:=\sum_{f\in\mathcal{L}}\Phi^f_{\ell s}$ and $d\log\bar{w}_{\ell s}:=\sum_{f\in\mathcal{L}}\frac{\Phi^f_{\ell s}}{\Phi^L_{\ell s}}d\log w^f_{\ell s}$ is a cost-shared weighted average. □

A.2.2 Factor Demands in the Quantitative Model

Consider the unit variable cost function of a firm in Section 2.2. Using Shephard's lemma, we derive the following expressions for the factor demands of a firm:

$$h=V_s(z;\frac{w^H_{\ell s}}{A^H_{\ell s}},\frac{w^L_{\ell s}}{A^L_{\ell s}},\frac{R}{A^K_s},y)^{\varphi_s}P_x^{\sigma_s-\varphi_s}(w^H_{\ell s}/A^H_{\ell s})^{-\sigma_s}y^{\bar{\epsilon}_s}$$
$$k=V_s(z;\frac{w^H_{\ell s}}{A^H_{\ell s}},\frac{w^L_{\ell s}}{A^L_{\ell s}},\frac{R}{A^K_s},y)^{\varphi_s}P_x^{\sigma_s-\varphi_s}(R/A^K_s)^{-\sigma_s}$$
$$l=V_s(z;\frac{w^H_{\ell s}}{A^H_{\ell s}},\frac{w^L_{\ell s}}{A^L_{\ell s}},\frac{R}{A^K_s},y)^{\varphi_s}(w^L_{\ell s}/A^L_{\ell s})^{-\varphi_s},$$

where $P_x^{1-\sigma_s}=(w^H_{\ell s}/A^H_{\ell s})^{1-\sigma_s}y^{\bar{\epsilon}_s}+(R/A^K_s)^{1-\sigma_s}$ is the ideal price index for the capital-skill bundle.

Using these factor demands, we can derive the following expressions for the capital-labor ratio and the high- to low-skill labor ratio:

$$\frac{k}{h+l}=\frac{P_x^{\sigma_s-\varphi_s}(R/A^K_s)^{-\sigma_s}}{P_x^{\sigma_s-\varphi_s}(w^H_{\ell s}/A^H_{\ell s})^{-\sigma_s}y^{\bar{\epsilon}_s}+(w^L_{\ell s}/A^L_{\ell s})^{-\varphi_s}}\quad\text{and}\quad\frac{h}{l}=\frac{P_X^{\sigma_s-\varphi_s}(w^H_{\ell s}/A^H_{\ell s})^{-\sigma_s}y^{\bar{\epsilon}_s}}{(w^L_{\ell s}/A^L_{\ell s})^{-\varphi_s}}.$$

Since both factor shares depend on y directly and through the price index P_x, the partial derivative of these shares with respect to firm scale is a function of factor cost shares and the three elasticities $(\sigma_s,\varphi_s,\bar{\epsilon}_s)$. We exploit the fact that the way these factor ratios vary with firms scale depends on $(\sigma_s,\varphi_s,\bar{\epsilon}_s)$ to estimate these elasticities in Section 3.

A.3 Endogenous Local Fundamentals

A long literature suggests that local productivities and amenities may be endogenous functions of the size and composition of a location's workforce. In our main calibration, we abstracted from such *agglomeration* effects. In an extension, we allow productivity terms and amenity terms to respond endogenously to indicators of local economic activity.

For productivity, Ahlfeldt and Pietrostefani (2019) provides a meta-study that collects estimates of the strength of agglomeration effects from a large set of published papers in the economic literature. We change the specification of local labor productivity for type-f workers in our model as follows:

$$A^f_{\ell st} = \bar{A}^f_{\ell st}(X^L_{\ell t})^{\chi_2},$$

where X^L_{ℓ} indicates the total population count in location ℓ at time t, the sum of high- and low-skill workers. We follow Ahlfeldt and Pietrostefani (2019) in setting $\chi_2 = 0.04$. Column 5 of Table 3 presents the resulting wage-density gradients in 2015.

Diamond (2016) provides direct evidence that amenities for high-skill workers are an increasing function of the share of high-skill workers in a location. We change the location amenity term for high-skill workers in our model to incorporate that channel by setting $\bar{B}^H_{\ell t} = \tilde{B}^H_{\ell t}\phi^{\chi_1}_{\ell t}$, where $\phi_{\ell t}$ is the ratio of college- to non-college-educated workers in location ℓ at time t. We borrow the parameter $\chi_1 = 2.6$ from Diamond (2016). Note that we do not need to re-calibrate our model; we can simply decompose the calibrated amenities into an endogenous and an exogenous part ($\tilde{B}^H_{\ell t}$). Column 6 of Table 3 presents the resulting wage-density gradients in 2015.

B. Additional Figures and Tables

In this section, we present additional figures and tables referenced in the main text.

B.1 Supporting Evidence for Section 1.2

This section provides additional evidence supporting the urban-biased growth patterns documented in Section 1.2.

Urban-Biased Growth in Other Datasets. Figure 2 in the main text uses data from the Longitudinal Business Database (LBD) to document urban-biased wage growth. Figure OA.1 replicates this result using alternative data sources. Panel A reproduces the LBD result for reference. Panel B uses the US Decennial Census; while the pattern persists, the gradient is somewhat attenuated, likely due to noise in self-reported wages. Panel C draws on the Quarterly Census of Employment and Wages (QCEW), an administrative dataset based on unemployment insurance records, and closely mirrors the LBD result, suggesting that the gradient is not specific to tax-based data. Panel D uses County Business Patterns (CBP), a public-use version of the LBD, and again finds a similar pattern. Together, these replications confirm that urban-biased growth is robust across datasets and not driven by a particular sample or measurement approach.

Wage Growth across other Commuting Zone Orderings. In the main text, we sort commuting zones into deciles based on 1980 population density using LBD data. Here, we replicate the wage growth patterns using US Decennial Census data and alternative commuting zone orderings. Figure OA.2 presents these results. Panel A ranks commuting zones by population density measured in the Census rather than the LBD. Panel B orders them by total population size. Panel C uses a tract-weighted density measure, aggregating census tract densities to the commuting zone level using population weights. Panel D ranks commuting zones by their average wage in 1980. Consistent with Giannone (2022), this alternative yields a flat pattern of wage growth, reflecting that high-wage cities in 1980 were not necessarily the most densely populated.

Urban-Biased Growth before 1980. Figure 1 in the main text documents strongly urban-biased wage growth between 1980 and 2015. To extend this analysis to earlier decades, we replicate the figure using US Decennial Census and ACS data going back to 1950. As shown in Figure OA.3, wage growth between 1950 and 1980 was only slightly biased towards dense locations, with urban-biased growth concentrated primarily in Business Services. The sharp increase in the wage-density gradient after 1980 marks a clear structural break, coinciding with the acceleration in the decline of IT capital prices. Because this exercise uses Census data rather than LBD data, the 1980 and 2015 values differ slightly from those in Figure 1.

Measuring Urban-Biased Growth using the Wage-Density Gradient. In the main text, we documented wage growth across commuting zone deciles ranked by 1980 population density. An alternative approach is to trace the evolution of the wage-density gradient—the coefficient from a cross-sectional regression of log average wages on log population density. This elasticity, commonly studied in urban economics, captures the degree to which wages vary with density across locations.

Figure OA.4 plots the evolution of this gradient using QCEW data. The elasticity more than doubled between 1980 and 2008 and has remained stable since then, reflecting the urban-biased growth pattern shown in Figure 2. To assess whether this trend holds across the distribution, we also estimate quantile regressions of log wages on log density. The resulting coefficients show that the increase in the wage-density gradient reflects a broad-based shift, not just changes in the upper tail. In each year, we recalculate the density of each commuting zone to reflect current population levels.

Changes in the Wage-Density Gradient Across Datasets. The rise in the wage-density gradient appears consistently in the main US labor market datasets. Figure OA.5a plots estimates from the QCEW, LBD, Decennial Census/ACS, and CBP. The QCEW, CBP, and LBD show similar levels and trends: the gradient rises sharply from 1980 to 2000 and then remains broadly stable. The Census and ACS yield lower point estimates—likely due to measurement differences—but show the same pattern over time.

Changes in the Wage-Density Gradient for Different Density Measures. The rise in the wage-density elasticity looks similar across alternative definitions of location density, and also holds for the elasticity of wages with respect to population size. Figure OA.5b plots estimates from the QCEW using four specifications. First, we fix population density at its 1980 level instead of updating it annually, as in Figure OA.4. Second, we use employment density in place of population density. Third, we measure tract-weighted population density in 1980, which downweights sparsely populated areas within a commuting zone. Fourth, we estimate the wage-population elasticity using 1980 commuting zone populations. All four measures show similar trends over time, confirming that the results do not depend on a particular density metric.

The Evolution of the Wage-Density Gradient Across US Counties. Figure OA.5c shows the wage-density elasticity estimated across counties using QCEW data. The level is lower than in the commuting zone estimates, but the trend over time is similar.

The Evolution of the Wage-Density Gradient in Europe. Figure OA.5d shows the wage-population gradient across locations in the EU-15, using GDP per worker as the outcome and total population as the regressor. We use population rather than density because of missing area data. The elasticity roughly doubles from 0.04 in 1980 to 0.08 in 2010, mirroring the trend observed in the US.

The Evolution of the Wage-Density Gradient in Microdata. Figure OA.6 complements the evidence from the time series shown above by showing the full cross-sectional relationship between log wages and log population density across commuting zones in 1980 and 2015. We plot separate scatter plots for Business Services and other sectors, using data from the Decennial Census and ACS. These plots make the steepening of the wage-density gradient over time visually transparent.

B.2 Supporting Evidence for Section 1.3: Accounting for Urban-Biased Growth

This section presents additional figures and exhibits for Section 1.3 in the paper which highlighted the role of Business Services and large establishments in accounting for the urban-biased growth in the data.

Disaggregated Industry Detail within Sectors. The main decomposition in Figure 4 uses 1-digit NAICS sectors. Figure OA.7 replicates this analysis at the 2-digit NAICS level. Within Business Services, the industries that contribute most to urban-biased growth are in the following order: Professional Services, Finance, Information, Administrative and Waste Services, Management of Companies, and Real Estate.

IT Capital Stocks per Worker across 2-Digit NAICS Industries. Figure 7 showed IT capital stocks per worker for each 1-digit NAICS sector. Figure OA.8 replicates this at the 2-digit level. Nearly all sub-industries within Business Services have higher IT capital per worker than any other industry. Outside of Business Services, the industries with the highest IT capital stocks per worker are Natural Resources and Utilities in 1980, and Natural Resources, Utilities, and Wholesale in 2015 (see also Ganapati, 2025).

Employment and Wages at Large and Small Establishments. Figure 5 in the paper showed that wage growth at large Business Services establishments accounts for most of the observed urban-biased growth. This section provides additional details.

Due to US Census disclosure restrictions, we define Business Services here as NAICS 51, 52, 54, and 55—excluding Real Estate and Administrative Services relative to the broader definition in the paper. We also redefine large establishments as those jointly employing the top 50% of US workers in 2015, resulting in a size cut-off of 200 workers (the main text used a 1980-based cut-off).

Figure OA.9 shows wages and employment shares at large and small establishments across commuting zones, sectors, and years. Panel A plots wages at large and small Business Services establishments in 1980 and 2015; Panel B does the same for other sectors. Panel C shows employment shares by commuting zone decile for large and small Business Services establishments; Panel D does the same for other sectors.

The figure helps explain why large Business Services establishments drive urban-biased wage growth. Panel A shows steep wage growth gradients across commuting zones for large Business Services firms. Panel C shows that these firms also have a larger employment share in dense areas. But these employment share differences are modest relative to the wage growth gradient in Panel A. Moreover, Panel D shows that employment shares by density remain stable over time, implying that differential shifts in employment are not the source of urban-biased growth. Instead, most of the effect is driven by within-firm wage growth at large Business Services establishments concentrated in dense locations.

Firms or Establishments and Urban-Biased Growth. Figure 5 in the main text decomposes urban-biased wage growth by establishment size. Establishments are classified as large or small based on whether they employ more or less than 108 workers, the size of the establishment employing the median US worker in 1980.

In this section, we implement an analogous decomposition using firm size instead. Specifically, we classify establishments based on whether they are controlled by firms above or below the 1980 firm-size median (approximately 1,000 workers).

For both definitions, we decompose wage growth in each location ℓ as:

$$\Delta w_\ell = \underbrace{\mu^L_{\ell O}\Delta w^L_{\ell O}}_{\text{O,L}} + \underbrace{\mu^S_{\ell O}\Delta w^S_{\ell O}}_{\text{O,S}} + \underbrace{\mu^L_{\ell N5}\Delta w^L_{\ell N5}}_{\text{N5,L}} + \underbrace{\mu^S_{\ell N5}\Delta w^S_{\ell N5}}_{\text{N5,S}} \quad + \underbrace{\sum_{se} w^e_{\ell s}\Delta\mu^e_{\ell s}}_{\text{S}} + \underbrace{\sum_{se} \Delta\mu^e_{\ell s}\Delta w^e_{\ell s}}_{\text{C}},$$

where $s \in \{O, N5\}$ denotes the sector (Other and Business Services) and $e \in \{L, S\}$ indicates large or small establishments or firms. $\mu^e_{\ell s}$ is the employment share and $w^e_{\ell s}$ the average wage for type e establishments/firms in sector s and location ℓ. The first four terms capture wage changes by sector and size; S captures sectoral shifts; C is a covariance term.

Figure OA.10a shows the decomposition using the definition based on firm size. Most urban-biased growth occurs at establishments of large Business Services firms. Figure OA.10b replicates the decomposition using the establishment-size definition and yields similar results.

The two decompositions lead to the same conclusion: large establishments in large Business Services firms account for most of the urban-biased wage growth in the US economy.

Non-IT Capital Stocks per Worker across 1-Digit NAICS Industries. Figure 7 in the paper showed IT capital stocks per worker across 1-digit NAICS sectors. Figure OA.11 replicates this figure for non-IT capital, defined as all private non-residential assets not classified as IT. Unlike in the case of IT capital, Business Services do not stand out in terms of capital stocks per worker other than information technology.

Aggregate Wage and Employment Growth in Business Services. Figure OA.12 shows the evolution of employment (left panel) and average wages (right panel), relative to 1980, in all 1-digit NAICS sectors. In both panels, we highlight Business Services in red.

Employment in Business Services more than doubled between 1980 and 2015, outpacing total US employment, which roughly doubled over the same period. Manufacturing is the only sector that experienced a decline.

The wages in Business Services also nearly doubled, while most other sectors saw increases of less than 40 percent.

Taken together, Figure OA.12 illustrates the rapid expansion of Business Services in both employment and earnings during the study period.

Price Declines. Figure OA.13 shows the BEA price indices for equipment (left panel) and intellectual property (right panel), relative to the BEA PCE deflator and normalized to 1980 levels. Both indices exhibit large declines between 1980 and 2020.

The decline is concentrated in specific components. For equipment, almost all of the drop reflects the falling prices of information processing equipment. For intellectual property, the decline is driven almost entirely by falling software prices.

These patterns motivate our focus on IT capital—defined as the sum of information processing equipment and software. Although the prices of non-IT capital have remained relatively stable since 1980, the price of IT capital has fallen sharply.

The Role of Cognitive Non-Routine Occupations. A large recent literature focuses on the role of occupations in employment polarization in the US (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, Sarte, and Schwartzman (2025) 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.

Figure OA.15 replicates Figure 6 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 *outside* Business Services exhibit wage growth that is largely unbiased across space. However, all occupations within Business Services experienced wage growth strongly biased toward denser labor markets. The figures suggest that the density bias in CNR wage growth is driven by the fact that Business Services industries employ a disproportionate amount of CNR workers, but is not particular to CNR occupations.

B.3 Additional Figures for Section 3: Quantification

This section presents additional data moments used to estimate the model in Section 3.

College Shares and Firm Size. The Current Population Survey (CPS) collects information on firm size, which we use to calculate the college share across the firm size distribution. Figure OA.14 plots the share of college-educated workers in firm-size bins. In both Business Services and other sectors, larger firms employ a higher share of college graduates. However, across all firm sizes, the college share in Business Services exceeds that in other sectors by about 15 percentage points. For each sector, we regress the college share on log firm employment and use the resulting coefficient to calibrate φ_s, the elasticity of substitution between high- and low-skill labor, as detailed in the text.

Commuting Zone Residential Rent Price Index. We construct a rent index for each commuting zone using microdata on gross rents and dwelling characteristics from the Decennial Census and ACS. We regress the log of gross rent on building age, number of rooms, and a commuting-zone-by-year fixed effect. We interpret the fixed effect as a price index for observationally equivalent housing in each commuting zone. The top two panels of Figure OA.16 plot the resulting rent index for 1980 and 2015. We normalize the index to 1 for the New York CZ in all panels.

B.4 Additional Figures for Section 4: Accounting for Urban-Biased Growth

This section presents additional model outputs referenced in the urban growth accounting exercise in Section 4.

Residential Rent Prices Across Commuting Zones in the IT-only Economy. The bottom left panel of Figure OA.16 shows residential rents across commuting zones in the model in 1980. These match the data exactly, as we calibrate the residential housing supply to replicate the observed rent index in each location.

The bottom right panel shows rents in the counterfactual IT-only economy in 2015. The rent-density gradient increases substantially, reflecting the impact of declining IT prices. In fact, the model predicts a steeper gradient than observed in the data, suggesting that forces outside the IT channel may have offset some of the rent divergence.

Large Firms and Urban-Biased Growth in the IT-only Economy. Figure OA.18 replicates Figure 5 in the top panel and shows the decomposition in the IT-only counterfactual in the bottom panel. As in the data, large firms account for most of the urban-biased growth.

However, the model does less well in matching the split between wage and employment growth. In the counterfactual, most of the urban-biased growth at large Business Services firms reflects differences in employment growth across locations, whereas in the data, wage growth plays a larger role. This gap reflects the assumption of the model that all firms in a location-sector pay the same wage. Introducing firm-specific labor supply curves could improve this fit, but is beyond the scope of the current paper.

Calibrated Amenity Residuals across Commuting Zones and Education Groups. Figure OA.17 plots the calibrated amenity residuals across commuting zones for 1980 and 2015, separately for college and non-college workers. Amenities are normalized to equal one in the New York commuting zone in 1980 for each education group.

Additional Accounting Results in the IT-only Economy. The main text quantifies how much of the rise in the wage-density gradient is accounted for by the IT-only counterfactual. Table OA.2 presents additional results and robustness checks.

Column 3 isolates the role of fundamental productivity. It updates productivity residuals from their 1980 to 2015 calibrated values, keeping the IT price and all other residuals fixed at 1980 levels. The wage-density gradient flattens in this scenario, reflecting rural-biased productivity growth for non-college workers, as shown in Figure OA.19. Column 4 instead updates only location-specific amenities, keeping all other structural elements constant. The wage-density coefficient remains flat, indicating that amenities did not play a role in generating urban-biased growth.

The remaining columns examine how the IT-only counterfactual performs under alternative parameter choices. In Column 5, we adopt a higher elasticity corresponding to $\sigma_s = 0.7$. In Column 6, we adopt a lower capital-labor elasticity, which implies a firm-level elasticity of substitution between skilled labor and capital of $\sigma_s = 0.5$. In Column 7, we test a model with equal labor-supply elasticities across education groups. Here, we set the spatial elasticity to 4 and the sectoral elasticity to 0.5, approximating the averages of our estimated values. In Column 8, we include a version of the counterfactual in which we set the substitution elasticities to the values used in Krusell et al. (2000) and in Column 9, we keep college shares constant at their 1980 values instead of letting them adjust.

Column 10 targets the elasticity of IT expenditure per unit of wage bill, based on estimates from Lashkari et al. (2024). Since Lashkari et al. (2024) does not report sector-specific elasticities, we target their gradient and the difference in gradients from the ACES data used in our baseline calibration.

B.5 The Relationship between Firm Scale and Capital Intensity.

In this section, we detail our construction of firm-level IT capital expenditures, present supplementary results, and benchmark our estimates against existing findings in the literature. We also highlight key conceptual differences between investment-based and stock-based measures of capital use.

Data Construction Our theory makes predictions about the relationship between IT capital *stocks* per worker at the firm level and how they vary with firm sales. To construct firm-level IT capital stocks, we use data from the US Census Bureau's Annual Capital Expenditure Survey (ACES) and its supplement, the Information and Communication Technology Survey (ICTS).

The ACES collects data on capitalized expenditures in structures and equipment—including software—for all domestic, private, non-farm firms between 2002 and 2015. Firms with more than 500 employees are always included in the sample, while smaller firms are selected probabilistically based on industry and payroll. The Census Bureau provides sample weights to ensure national representativeness. Although software investments are reported separately, the ACES does not distinguish information and communication hardware from other types of equipment. Consequently, our analysis of ACES data focuses on software.

The ICTS was conducted from 2004 to 2013 and collects data on both capitalized investments and non-capitalized expenditures across four ICT categories: (i) computers and peripherals, (ii) other ICT equipment, (iii) electro-medical apparatus, and (iv) computer software. The survey covers all domestic, private, non-farm firms with at least one employee and follows a sampling structure similar to that of the ACES. In our analysis of the ICTS, we focus on categories (i) and (iv)—that is, hardware and software.

We process the ACES and ICTS samples separately to construct IT capital stocks per worker. First, we merge each survey with the LBD using common firm identifiers. In both datasets, we restrict the sample to firms with non-missing and positive values for payroll, employment, and sales (as reported in the surveys, not the LBD). Although the surveys do not report capital stocks by asset category, they do include end-of-year total fixed assets for each firm. We drop firms with zero or missing values for this variable.

We construct firm-level IT capital stocks using a variant of the standard perpetual inventory method, adapted to the structure of our data. To "initiate" the method, we need to construct an initial IT capital stock for each firm. For a firm i in the survey, without previous years with investment data, we impute the IT capital stock in year t, K_{it}, from their observed investment at time t, I_{it}, using the usual "steady-state" formula:

$$K_{it} = I_{it}(1 + g_s)/(\delta_{st} + g_s),$$

where δ_{st} denotes the depreciation rate of IT capital, and g_s is the average growth rate of aggregate IT capital investment in sector s, calculated over the 2006–2015 period. The depreciation and growth rates are sourced from the Bureau of Labor Statistics (BLS) and computed separately for each sector.[30]

[30]We use the BLS Rental Prices table from the Total Factor Productivity and Related Measures section (https://www.bls.gov/productivity/tables/), which reports capital stocks, investment, depreciation rates, and rental prices by 4-digit NAICS industry and detailed capital asset. For the rental rate r_{st}, we use the "rental price used"; for the depreciation rate δ_{st}, the "wealth stock depreciation rate"; and for g_s, the average growth rate of capital investment from 2006 to 2015. We aggregate across assets and industries to construct all rates at the level of Business Services and a residual "Other" sector, weighting each asset–industry pair by its capital stock share. All computations are performed separately for software—defined as "Software, custom,"

For subsequent years, we construct firm-level capital stocks using the standard accumulation equation, combining the depreciated prior-year capital stock with the observed investment in the current period, I_{it}:

$$K_{it} = (1 - \delta_{st})K_{it-1} + I_{it}.$$

In years when a firm reports zero IT investment, we carry forward its capital stock as the depreciated value of the previous year. If the firm is not observed for a given year, we exclude the firm from the sample in that year and reintroduce it once positive investment is observed again.

To measure "flow" payments to IT capital in either data set, we combine capital stocks with capital rental rates obtained from the BLS.[31] We compute total payments to IT capital as the sum of rental payments, given by the product of the sector-year rental rate and the firm's IT stock, and non-capitalized one-off expenditures such as leases, subscriptions, or licensing fees, denoted by E_{it}:

$$IT_{it} = r_{st}K_{it} + E_{it}.$$

Here, IT_{it} represents total flow payments to IT capital for firm i in year t, and K_{it} is the capitalized stock. We compute IT_{it} separately for ACES (software only) and ICTS (hardware and software). Since the ACES does not report non-capitalized IT expenditures, E_{it} is only available in the ICTS. In the ICTS, we calculate capital payments for hardware and software separately and sum them to obtain total IT expenditure per worker. All nominal values are converted to 2015 dollars.[32]

Our regressions include commuting zone and industry fixed effects. For single-establishment firms, both industry and ZIP code are directly reported in the LBD, so their industry and commuting zone can be assigned without ambiguity. For multi-establishment firms, assigning a single industry or location requires additional assumptions when establishments span multiple industries or commuting zones. In these cases, we follow standard practices in the literature, applying assignment rules used in prior studies based on the same data.

We assign each multi-establishment firm to the commuting zone of its headquarters

"Software, own-account," and "Software, pre-packaged"—and hardware, which includes "Direct access storage devices," "Instruments: photocopying and related equipment," "Integrated systems," "Mainframe computers," "Personal Computers (PCs)," "Printers," "Storage devices," "Tape drives," and "Terminals."

[31] We use the "Rental Prices" table in the "Total Factor Productivity and Related Measures" section of the BLS website (see https://www.bls.gov/productivity/tables/). We use the variable "rental rates used," constructed by the BLS based on the standard user cost of capital formula:

$$r = [(P \times R) + (P \times D) - \Delta p]\,(1 - u \times z - k)/(1 - u),$$

where P is the asset deflator, R is the internal rate of return, D is the depreciation rate, and Δp is the expected capital gain (based on a three-year moving average of price changes). The tax adjustment term includes the corporate tax rate u, the investment tax credit rate k, and the present value z of depreciation allowances.

[32] Note that since rental rates vary only at the sector-year level, they do not meaningfully affect regressions that include detailed industry-year fixed effects.

following the procedure in Rubinton (2025). We identify the headquarters as the firm's largest establishment with a two-digit NAICS code 55 (Management of Companies). If no such establishment exists, we use the establishment with the highest average wage.[33]

To assign industry codes to multi-establishment firms, we follow Jiang and Rubinton (2024) and use the industry of the establishment with the largest employment share. As a robustness check, we implement a continuous classification that weights industry codes by each establishment's share in firm-wide employment. Both approaches yield similar results, as we show in the next section.

The Relationship between Capital per Worker and Firm Sales Table 1 reports regressions of log IT capital payments (IT_{it}) per worker on log sales, pooled across all firms and years in the respective sample. The regressions include an interaction between log sales and an indicator for whether the firm operates in the Business Services sector. All specifications control for firm age fixed effects and 6-digit NAICS industry fixed effects interacted with year, following Lashkari et al. (2024). Columns 1 and 3 additionally include commuting zone fixed effects interacted with year. Columns 2 and 4 further allow these commuting zone effects to vary by sector by interacting them with the Business Services indicator.

We find positive and statistically significant coefficients on log sales across all four regressions. The elasticity of IT capital per worker with respect to sales is approximately twice as large in Business Services compared to other sectors. The estimated coefficients are also larger when IT capital is measured using software only (ACES) rather than software and hardware (ICTS). Since the rental rate of capital varies only at the industry-year level, our inclusion of industry-year fixed effects absorbs this variation.[34] As a result, the coefficient on log sales captures the elasticity of the capital-labor ratio with respect to firm sales.

Table OA.3 reports regressions using an alternative, continuous measure of whether a multi-establishment firm operates in Business Services. Rather than assigning each firm to a single industry based on its largest establishment, we measure the share of total firm employment in establishments classified as Business Services. This measure is binary for single-establishment firms but becomes continuous for multi-establishment firms with mixed activity. The estimated coefficients on log sales remain similar under this alternative definition, indicating that our results are robust to how Business Services are defined.

Benchmarking to the Literature Lashkari et al. (2024) present comparable regressions to those in our Table 1 using French firm-level microdata. Their Table 1 reports separate estimates based on two types of variation: within-industry and within-firm. These correspond to different sets of fixed effects, industry-year fixed effects in the former and firm fixed effects (in addition to industry-year) in the latter. In all specifications, they distinguish between software and hardware capital and consistently find positive

[33] Results are robust to excluding firms without an identifiable headquarters.

[34] This relationship holds only approximately in the specification that incorporates non-capitalized payments.

coefficients on log sales. Their within-firm estimates are smaller than their within-industry estimates and of the same order of magnitude as our results. Their coefficients are larger than ours across all specifications.

Lashkari et al. (2024) also report ”causal” elasticity estimates using an instrumental variables strategy, placing the elasticity at approximately 0.3, slightly higher than ours but of a similar order of magnitude.[35] Their ”causal” and correlational within-firm estimates are very similar.

We view the similarity in magnitudes as an important confirmation of our approach. One key difference that may explain the slightly lower estimates in our US data is sample coverage. The French data used by Lashkari et al. (2024) include all firms with 20 or more employees on a continuous basis, whereas the US data continuously include only firms with at least 500 employees, with smaller firms sampled probabilistically. Because many IT assets may involve fixed costs, smaller firms are less likely to adopt them. As a result, including more small firms with correspondingly low IT capital stocks could steepen the estimated relationship between IT capital per worker and firm size.

For robustness, we recalibrate our model to target the coefficient estimates reported by Lashkari et al. (2024) instead of our own. When we rerun the main IT-only counterfactual using this alternative calibration, the stronger capital–scale complementarity implied by their estimates amplifies the effect of our mechanism (see Table OA.2). This is consistent with the fact that all log sales coefficients reported in their study exceed our baseline estimates. We discuss this robustness exercise in Section 4.

To our knowledge, the only other paper that studies how IT capital–labor ratios vary with firm size is Lashkari et al. (2024). This gap in the literature likely reflects the scarcity of firm-level data on IT investments or capital stocks in the United States. Within the US Census Bureau’s data infrastructure, the Annual Capital Expenditures Survey (ACES) and the Information and Communication Technology Survey (ICTS) are, to our knowledge, the only sources that contain such information.

Discussion: Capital Stocks versus Capital Investments Our analysis requires inferring firm-level IT capital stocks from observed investments using the perpetual inventory method. This is essential because the theory makes direct predictions about stocks, not investment flows. By contrast, recent studies using the ACES and ICTS datasets focus on IT investment patterns across firms.

In an important contribution, Jiang and Rubinton (2024) study *investments* in custom software across firms.[36] Their findings underscore the importance of distinguishing between capital stocks and investment flows. They show that, conditional on investing in a given period, firms with more establishments allocate a smaller share of their total investment to custom software. At the same time, larger firms are much more likely to

[35] The estimation of the causal elasticity requires more structure and reflects the elasticity of the ratio of payments to IT capital relative to labor and non-IT capital inputs to firm sales.

[36] Custom software is a subcategory of the software studied in this paper.

invest in custom software in any given year.

The asymmetry in investment frequency between large and small firms highlights why measuring stocks—not flows—is central to our analysis. Large firms accumulate IT capital steadily, while smaller firms invest more sporadically. As a result, investment per worker rises with firm size, but less sharply than capital stocks, as shown in Figure 1 of Lashkari et al. (2024).

Our findings are fully consistent with Jiang and Rubinton (2024): the capital stocks we construct capture both the extensive and intensive margins by accumulating investments over time. Because larger firms invest more regularly, they hold more IT capital and have higher flow expenditures per worker.

A final distinction between our approaches concerns scope. While Jiang and Rubinton (2024) focus on custom software, which they argue is non-rival, we include all categories of software (and hardware). The non-custom software in our measure likely involves headcount-specific licenses, making it excludable and thus more comparable to traditional capital.

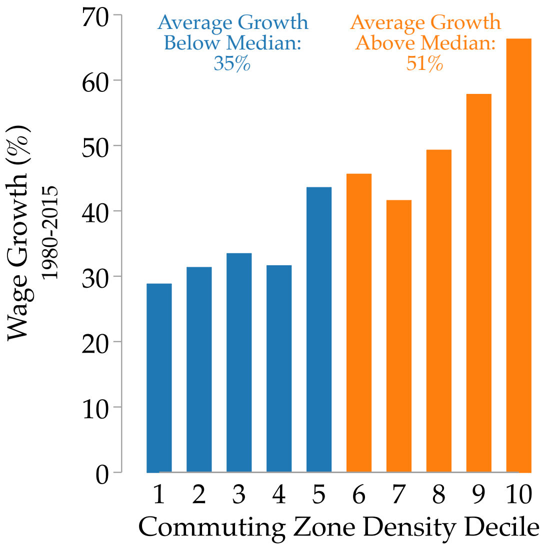
TABLE OA.1: SECTORAL AND SPATIAL LABOR-SUPPLY ELASTICITIES

	(1) College	(2) Non-College	(3) College	(4) Non-College
PANEL A: SECTORAL ELASTICITIES				
Δ log(Wage)	0.467	1.016	1.106	0.572
	(0.103)	(0.0433)	(0.192)	(0.0896)
N	17713	17782	17713	17782
First Stage F	182.6	2055.5	176.0	789.8
Fixed Effect: Year-Commuting-Zone	✓	✓	✓	✓
Commuting Zone Pop. Weighted			✓	✓
PANEL B: SPATIAL ELASTICITIES				
Δ log(Deflated Wage Index)	4.807	3.425		
	(1.087)	(1.735)		
Δ log(Wage Index)			4.253	2.989
			(0.926)	(0.537)
N	2223	2223	516	516
First Stage F	19.56	3.895	27.84	37.52
Fixed Effect: Year	✓	✓	✓	✓
Instrumented Rent			✓	✓

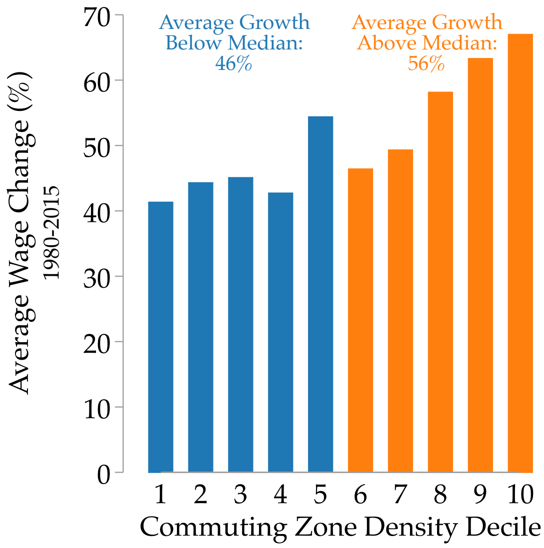
Notes: $p < 0.05$, $p < 0.01$, $p < 0.001$. Robust standard errors in parentheses. This table implements the structural labor supply equations for locations and sectors in the data. The underlying data comes from the US Decennial Census Files and, after 2000, from the American Community Survey. We run regressions in decadal differences and instruments for wage changes using the instrumental variables described in the body of the paper. Panel A shows the regressions for the sectoral labor supply elasticities based on equation (13). Columns 1 and 2 show coefficient estimates from a regression that uses data on all NAICS 1-digit sectors. Columns 3 and 4 show the same regressions but weights by commuting zone population in 1980. Panel B shows the regressions for the spatial labor supply elasticities based on equation (14). Columns 1 and 2 show coefficient estimates from a regression that uses our full sample. Columns 3 and 4 show estimates that follow the two-instrument procedure in Diamond (2016) and use a smaller sample for which the requisite data is available.

FIGURE OA.1: URBAN-BIASED GROWTH ACROSS DATASETS

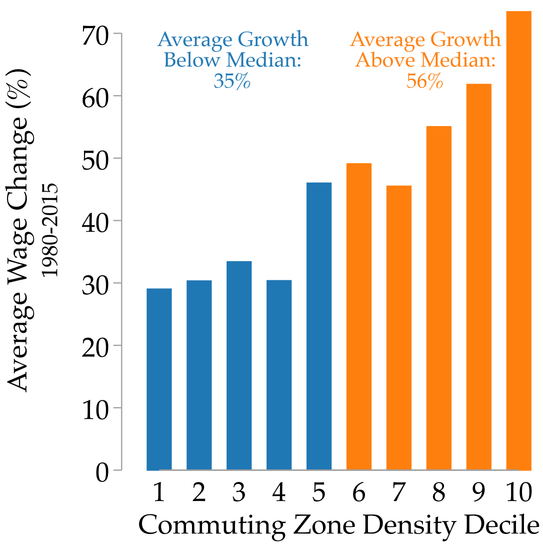
(A) LBD-Baseline



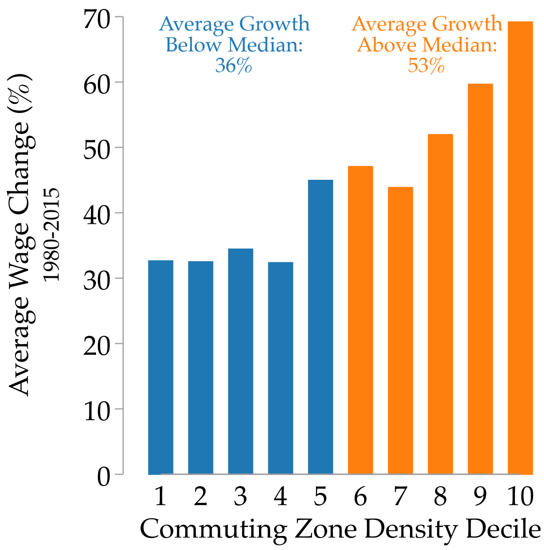
(B) Census/ACS



(C) QCEW

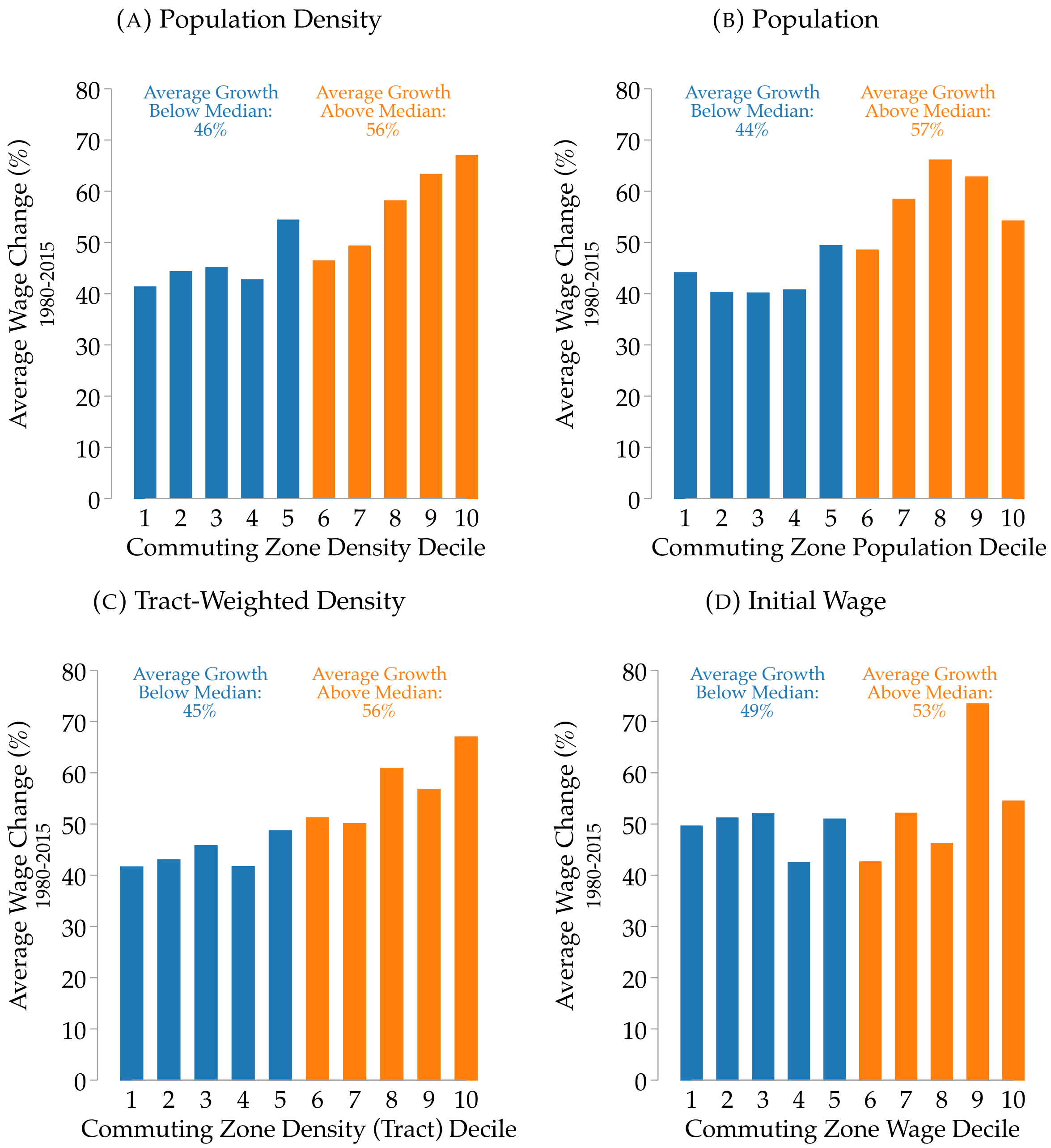


(D) County Business Patterns



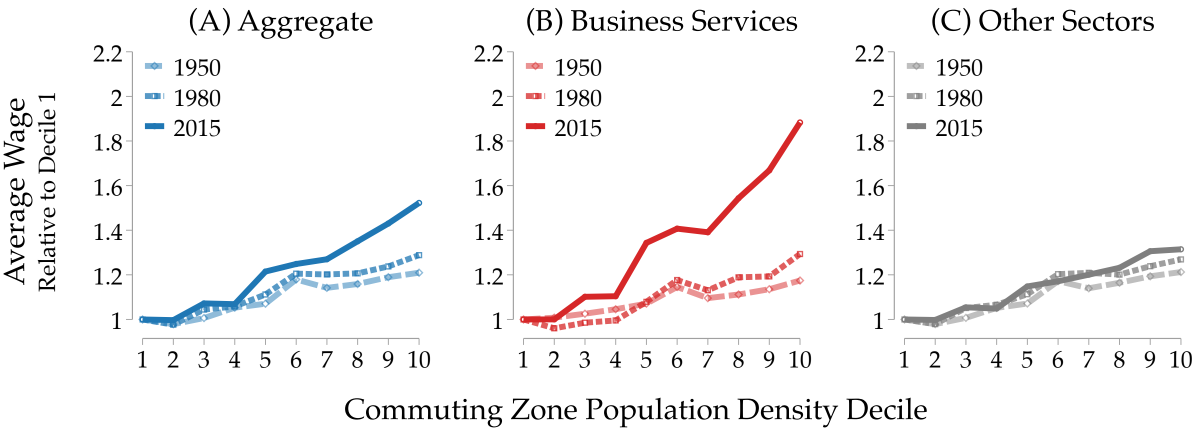
Notes: This figure shows wage growth between 1980 and 2015 across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density across four different data sets. Each decile accounts for one-tenth of the US population in 1980. Panel A uses data that comes from the US Census Bureau's LBD and covers all US private, non-farm employer establishments. Panel B uses data from the US Census Bureau's 1980 Decennial Census and the 2015 American Community Survey. Panel C uses data from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. Panel D uses US Census County Business Patterns data, which contain tabulated values from the LBD. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

FIGURE OA.2: SPATIALLY-BIASED WAGE GROWTH



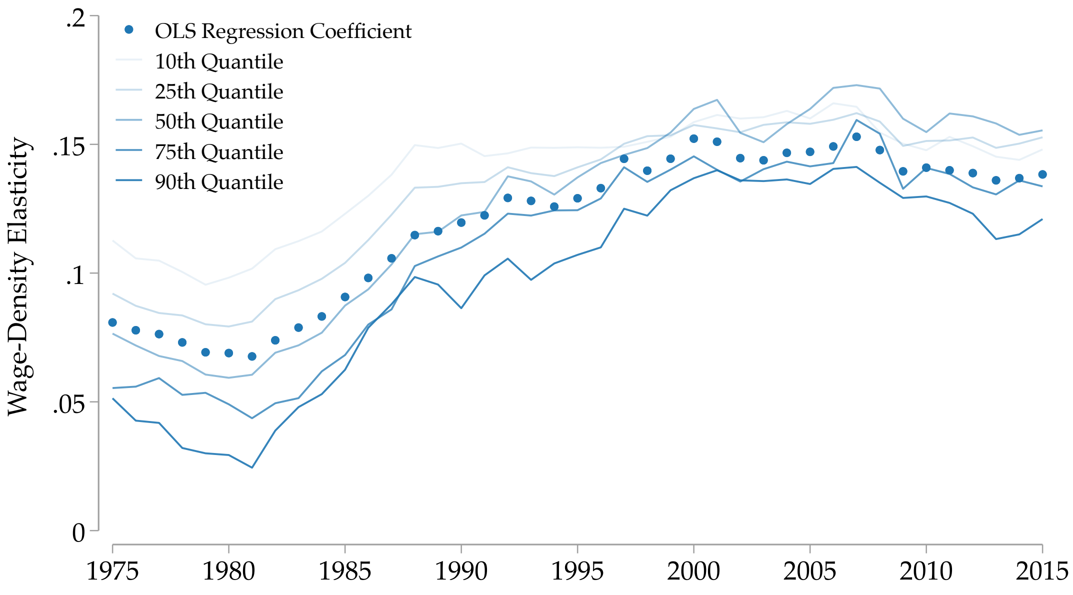
Notes: This figure shows wage growth between 1980 and 2015 across commuting zones (Tolbert and Sizer, 1996) sorted in four different ways. Each decile accounts for one-tenth of the US population in 1980. The underlying data come from the US Census Bureau's LBD and cover all US private, non-farm employer establishments. Panel A replicates the original ordering of commuting zones by initial population density. Panel B orders US commuting zones by initial aggregate population. Panel C uses tract-weighted population density using 1990 data (the first year with complete coverage). Panel D orders commuting zones by initial 1980 wage levels. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

FIGURE OA.3: THE US WAGE-DENSITY GRADIENT IN 1950, 1980, AND 2015



Notes: This figure shows average annual wages across commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density, separately for 1950, 1980 and 2015. Each decile accounts for one-tenth of the US population in 1980. The underlying data come from the US Census Bureau's Decennial Census for 1950 and 1980 and the 2015 American Community Survey. Each decile accounts for one-tenth of the US population in 1980. The first decile corresponds to 10 $people/mi^2$ and the tenth decile corresponds to 2300 $people/mi^2$. We show all wages relative to wages in decile 1.

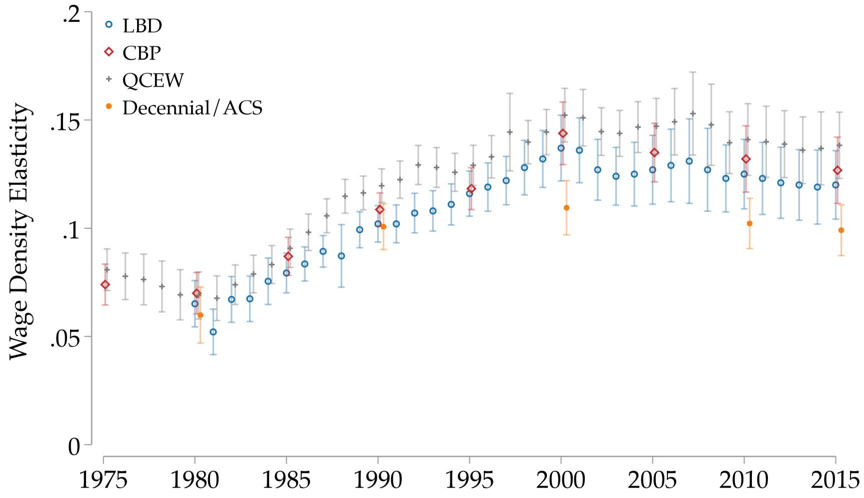
FIGURE OA.4: THE US WAGE-DENSITY GRADIENT OVER TIME



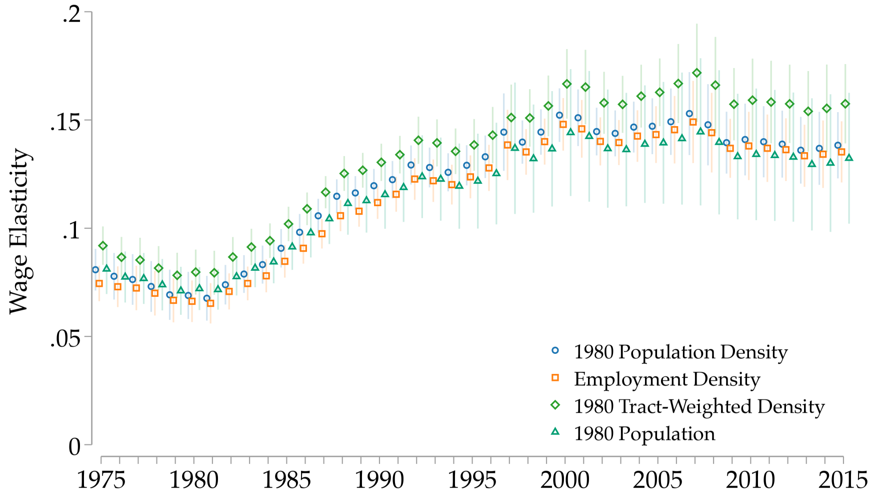
Notes: This figure shows coefficients from a regression of log average wages on log population density run separately for each year between 1975 and 2015 across US commuting zones (blue dots), weighted by 1980 population. We use the US Bureau of Labor Statistics' Quarterly Census of Employment and Wages for wage data for private employers. The lines show the coefficients from quantile regressions at the 10th, 25th, 50th, 75th, and 90th quantiles each year.

FIGURE OA.5: THE US WAGE-DENSITY GRADIENT ROBUSTNESS

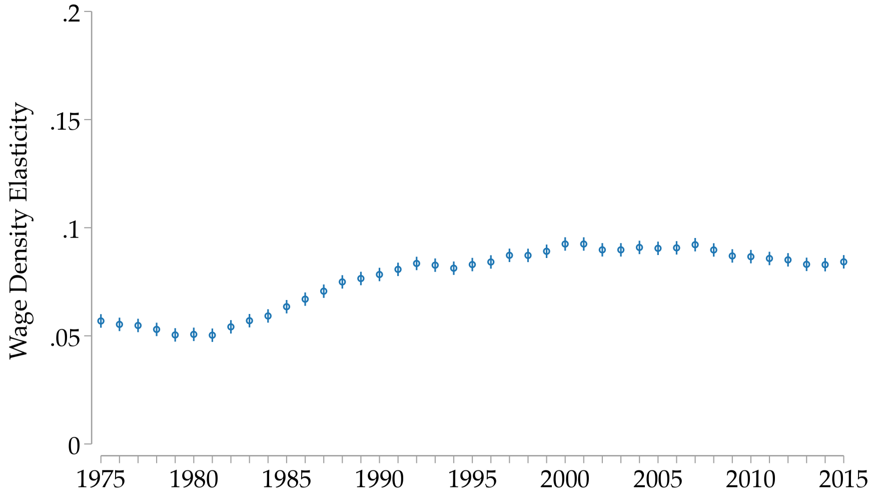
(A) Comparing Data Sources



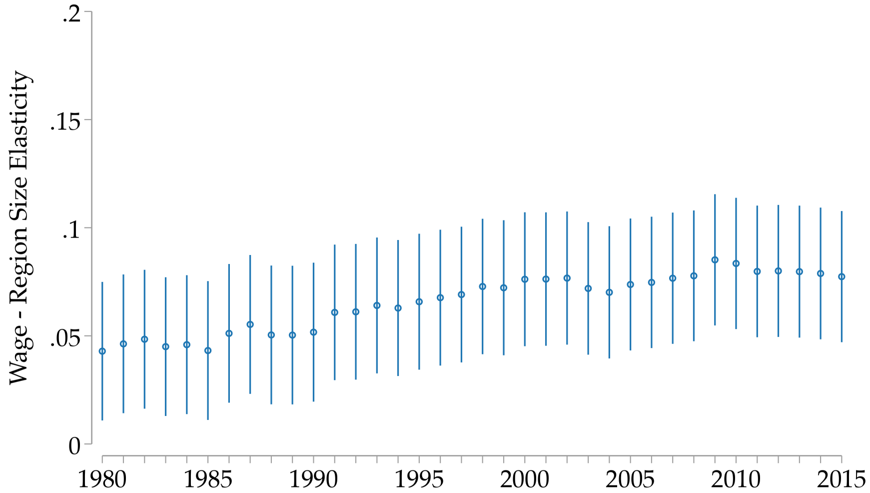
(B) Comparing Density Measures - QCEW



(C) County-Level Data - QCEW

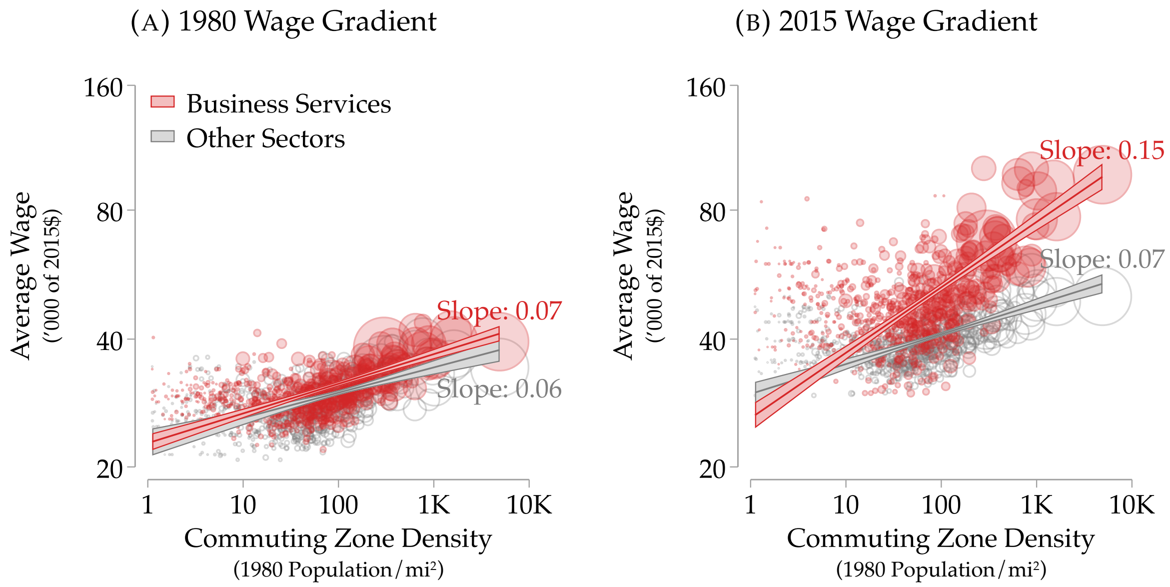


(D) European Union (15) Data



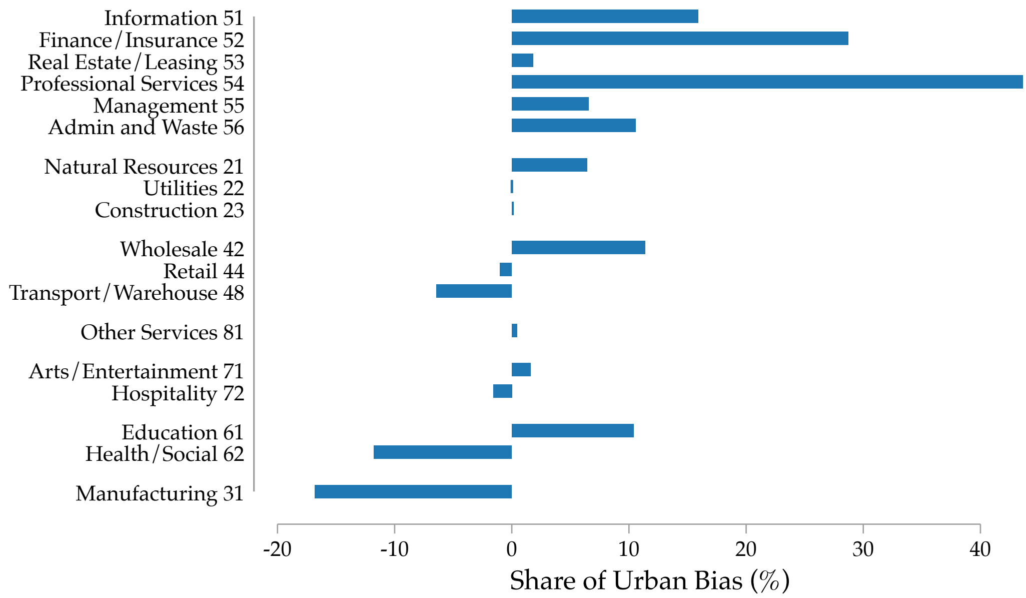
Notes: Panel A shows the wage density elasticity computed across commuting zones in four different datasets: the US Census' LBD, the US Census' County Business Patterns, the US Bureau of Labor Statistics' Quarterly Census of Employment and Wages, and the US Decennial Census and the American Community Survey. Panel B shows the wage-density elasticity across commuting zones for different measures of density and the wage-population elasticity. Panel C shows the wage-density elasticity across counties computed in the US Bureau of Labor Statistics Quarterly Census of Employment and Wages. Panel D shows the elasticity of GDP per worker to population density for a group of 15 European countries using data from Ehrlich and Overman (2020).

Figure OA.6: The Wage-Density Gradient by Sector in 1980 and 2015



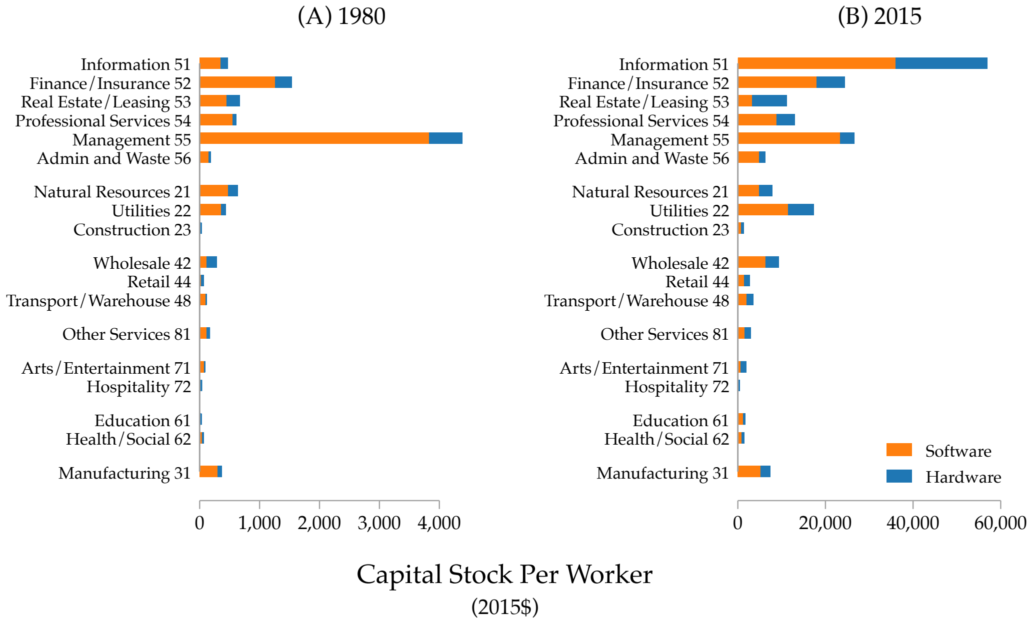
Notes: The figure shows the wage-density gradient across commuting zones for Business Services and the rest of the economy in 1980 and 2015. The figure uses 1980 US Decennial Census data and 2015 American Community Survey data. Panel A shows the wage-density elasticity for both sectors in 1980; the same gradient is shown in 2015 in Panel B. The size of the dots is proportional to the 1980 commuting zone population. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

Figure OA.7: Sectoral Origins of Urban-Biased Wage Growth across NAICS-2 Industries



Notes: The figure decomposes the difference in 1980–2015 wage growth between commuting zones with above-median and below-median densities in 1980 into the contributions of each NAICS-2 sector. The blue bars show the share of the wage growth difference accounted for by each sector (cf. equation (2)). The underlying data come from the US Census Bureau's LBD and cover all US private, non-farm employer establishments. We classify above-median density commuting zones as the highest density commuting zones jointly accounting for 50% of 1980 employment. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

FIGURE OA.8: IT CAPITAL STOCK ACROSS NAICS-2 INDUSTRIES



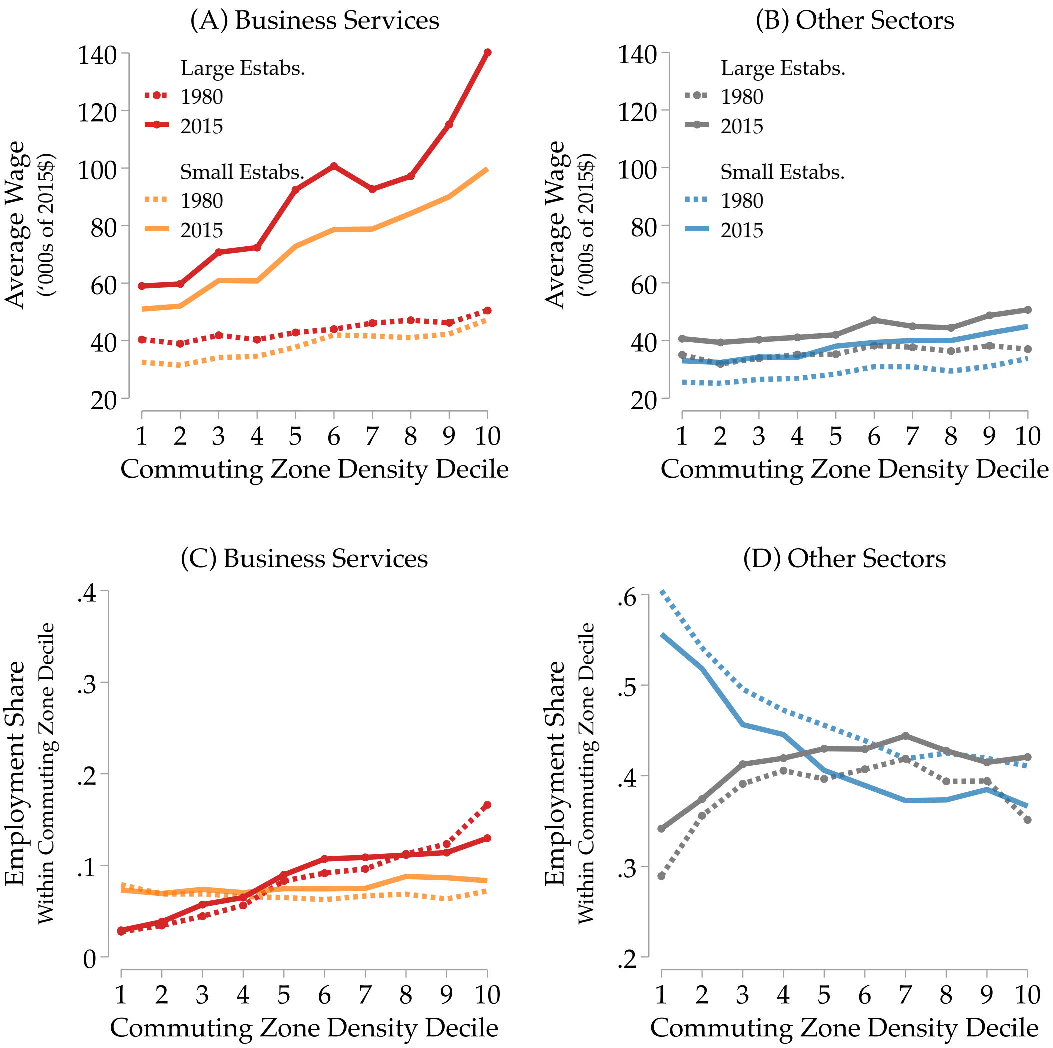
Notes: The figure shows capital stock per worker for different information technology assets across 2-digit NAICS sectors in 1980 and 2015. Data on capital stock in each sector are from the BEA. Data on employment in each sector are from the Quarterly Census of Employment and Wages. Software refers BEA codes ENS1–ENS3 and hardware to EP1A-EP31. Sectors appear in order of their contribution to urban-biased growth. All values are adjusted using the BEA's asset-specific price deflators to 2015 dollars.

TABLE OA.2: URBAN-BIASED GROWTH ROBUSTNESS EXERCISES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	10)
	Data		Struc. Resid.		Subs. Elas.		Equal Labor	KORV	Const. Pop.	Lashkari
	1980	2015	Prod.	Amen.	High	Low	Supp. Elast.	Elast.	Share	et. al.
Business Services	0.070	0.154	-0.019	0.073	0.235	0.123	0.133	0.123	0.126	0.143
Other Sectors	0.060	0.070	0.050	0.063	0.077	0.070	0.071	0.075	0.068	0.071
Aggregate	0.063	0.102	0.043	0.067	0.139	0.088	0.091	0.096	0.085	0.094
Δ Aggregate		0.039	-0.022	0.001	0.076	0.024	0.032	0.032	0.022	0.031

Notes: This table shows the regressions of log average wages on log population density in the cross-section of US commuting zones in the data and in various counterfactual economies. Note that the 1980 cross-section is the same in the data and the IT-only economy. The "data" columns come from the 1980 Decennial Census and the 2015 American Community Survey. Column 3 shows the wage-density elasticity in 2015 if only productivity residuals had varied and all other structural residuals and parameters were fixed at their 1980 values. Column 4 shows the wage-density elasticity in 2015 if only amenity residuals had varied and all other structural residuals and parameters were fixed at their 1980 values. Column 5 shows the wage-density elasticity in 2015 in the IT-only economy exercise; we choose $\sigma_s = 0.7$ from Karabarbounis and Neiman (2014). Column 6 shows the wage-density elasticity in 2015 in the IT-only economy exercise; however, we choose $\sigma = 0.5$. Column 7 shows the wage-density elasticity in 2015 in the IT-only economy exercise; however, we set labor supply elasticities for college- and non-college-educated workers equal to the mean calibrated elasticity for these groups so that both groups have the same elasticity. Column 8 uses the substitution parameters from Krusell et al. (2000) and recalibrates the model. Column 9 fixes the share of college educated and non-college workers to the 1980 levels. Column 10 uses estimates of the elasticity of IT expenditure per unit of the wage bill from Lashkari et al. (2024) to target ϵ_s .

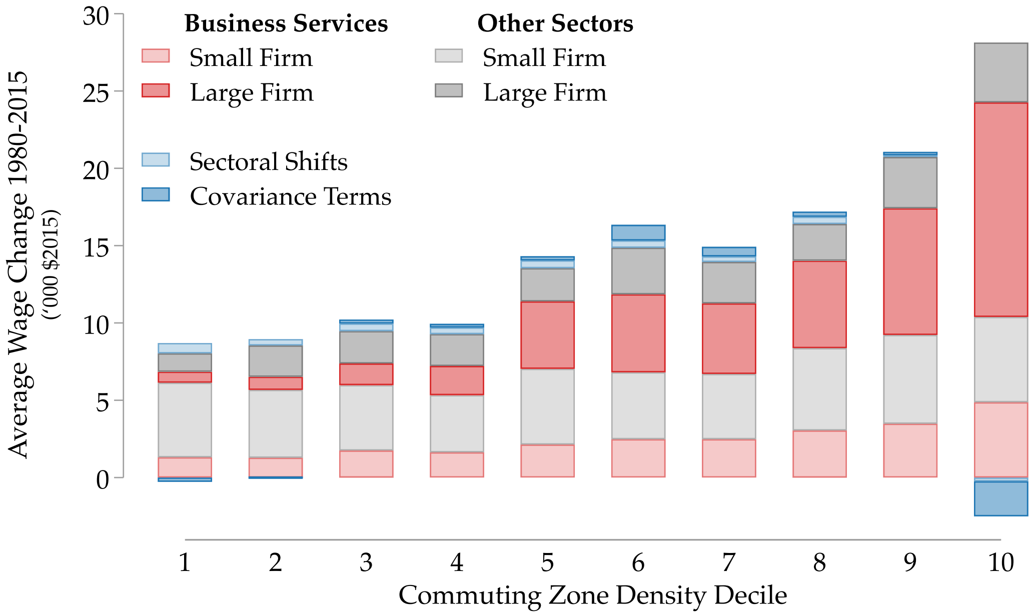
FIGURE OA.9: EMPLOYMENT AND WAGES AT LARGE AND SMALL ESTABLISHMENTS



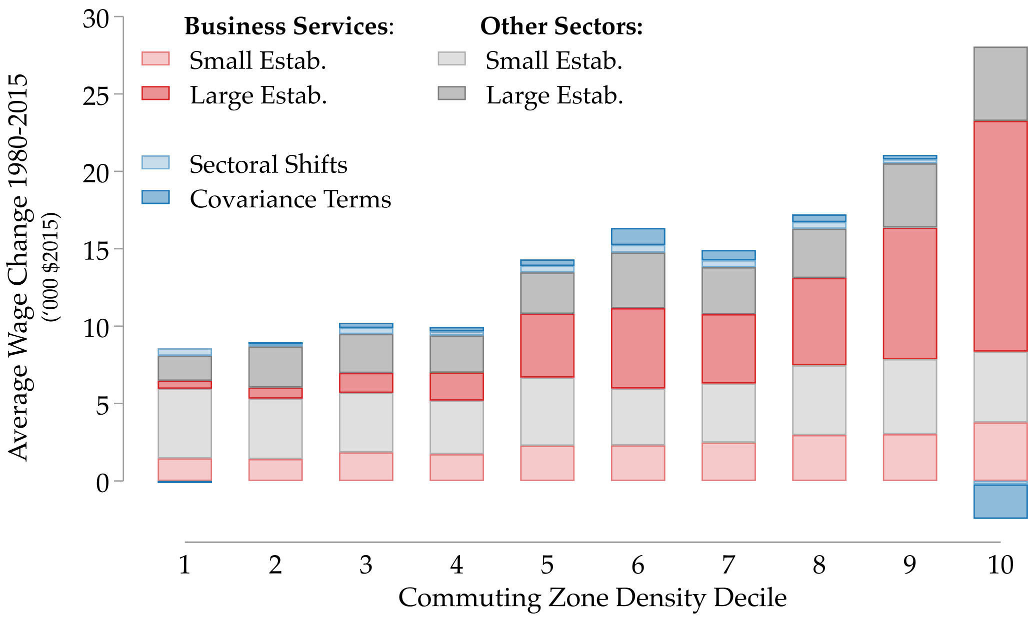
Notes: The figure shows average wages and employment shares by sector and establishment size across commuting zone deciles ordered by population density, for 1980 and 2015. Each decile accounts for one-tenth of the US population in 1980. The top row reports average wages at large and small establishments in Business Services (Panel A) and other sectors (Panel B). The bottom row shows the corresponding employment shares (Panels C and D). Solid lines refer to 2015, dashed lines to 1980. Data are from the US Census Bureau's LBD and cover all private, non-farm employer establishments. Wages are measured as average payroll per worker, computed by aggregating establishment-level payroll and employment within each commuting zone and sector. Business Services includes NAICS 51, 52, 54, and 55. Due to disclosure constraints, we exclude NAICS 53 and 56. Establishments with 108 or more employees are classified as large; they account for 47% of employment in 1980 and 50% in 2015. All values are in 2015 dollars, deflated using the BEA PCE price index.

FIGURE OA.10: THE ROLE OF LARGE FIRMS AND ESTABLISHMENTS FOR WAGE CHANGES WITHIN COMMUTING ZONES

(A) The Role of Large Firms

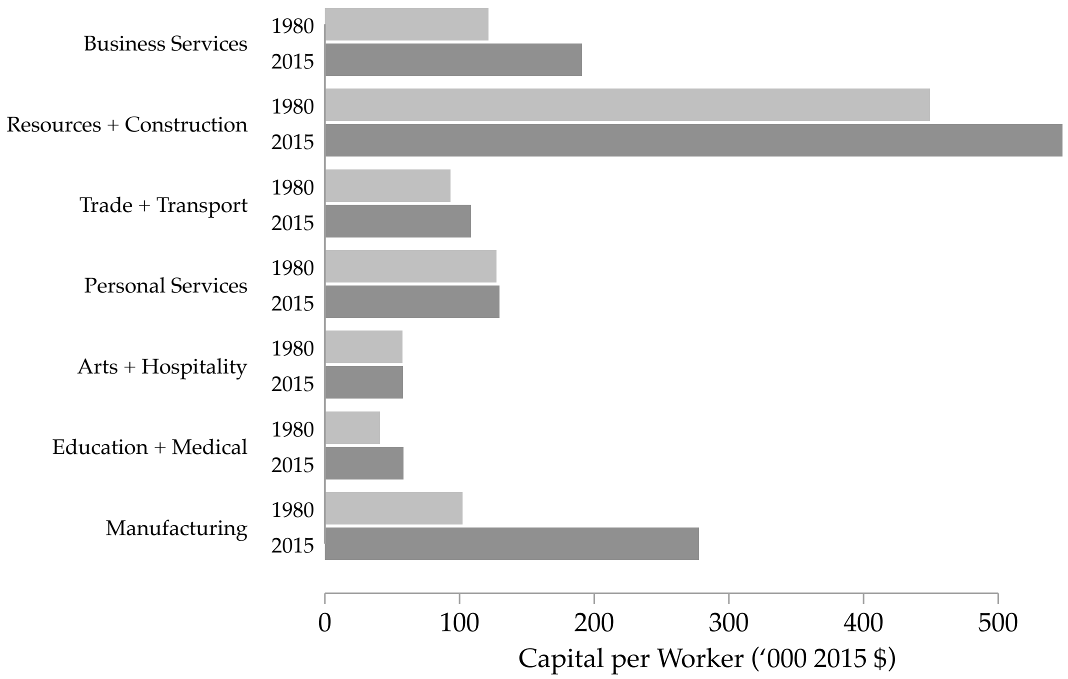


(B) The Role of Large Establishments



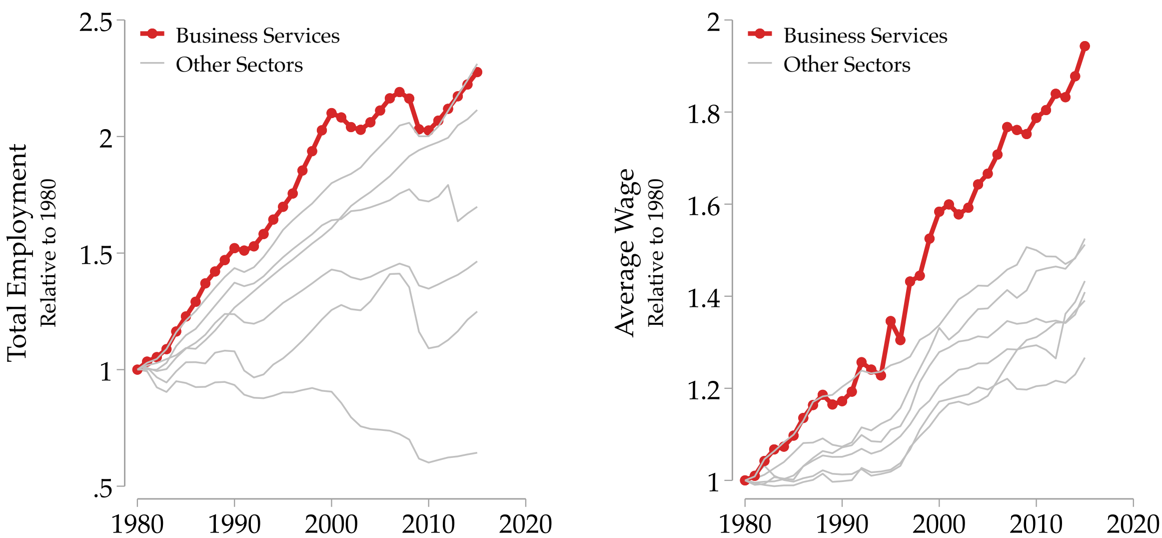
Notes: The figure decomposes wage changes within commuting zones (Tolbert and Sizer, 1996) sorted into deciles of increasing population density into wage changes due to large and small firms (Panel A) and large and small establishments (Panel B). Each decile accounts for one-tenth of the US population in 1980. The underlying data come from the LBD. We compute average wages as average payroll per worker by aggregating establishment payroll numbers and employment counts across all establishments in a commuting zone and sector. In the top panel, we classify establishments belonging to large firms as those with at least 1,000 employees in their sector (Business Services versus Other Sectors). Such firms account for roughly 44% of US employment in 1980 and 47% in 2015. To compute the decomposition, Business Services firms are those with employment at establishments coded as NAICS 51, 52, 54, 55; due to disclosure reasons, we omit NAICS 53 and 56 here. In the bottom panel, we classify large establishments as those with at least 200 employees, accounting for 47% of all employment in 1980 and 50% in 2015. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

FIGURE OA.11: AGGREGATE NON-IT CAPITAL STOCK BY SECTOR



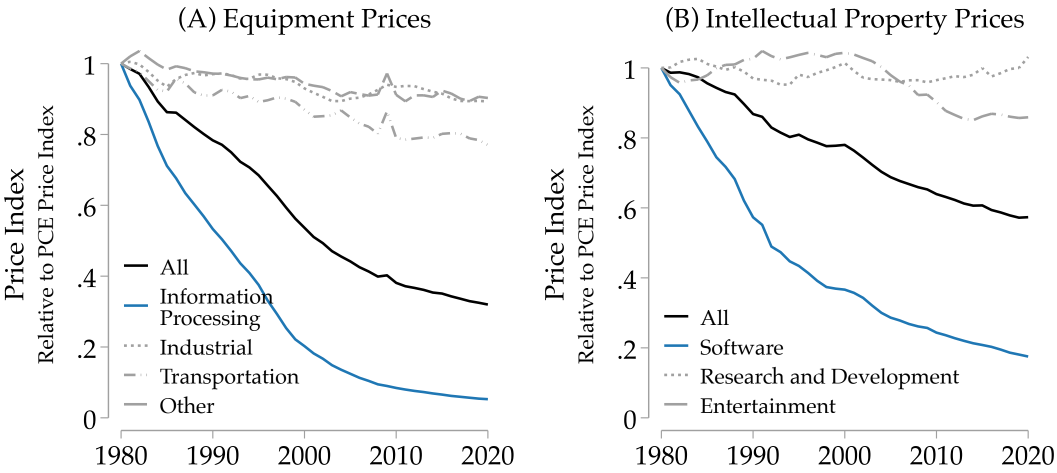
Notes: The figure shows capital stocks per worker for different non-IT capital assets across 1-digit NAICS sectors in 1980 and 2015. Data on capital investments in each sector are from the BEA. Data on employment in each sector are from the Quarterly Census of Employment and Wages. We define non-IT capital as all non-structures capital except the following "IT codes:" Software refers to BEA codes ENS1, ENS2 and ENS3, and hardware to EP1A-EP31. Sectors appear in order of their contribution to urban-biased growth. All values are adjusted using the BEA's asset-specific price deflators to 2015 dollars.

FIGURE OA.12: AGGREGATE WAGE AND EMPLOYMENT GROWTH BY SECTOR, 1980–2015



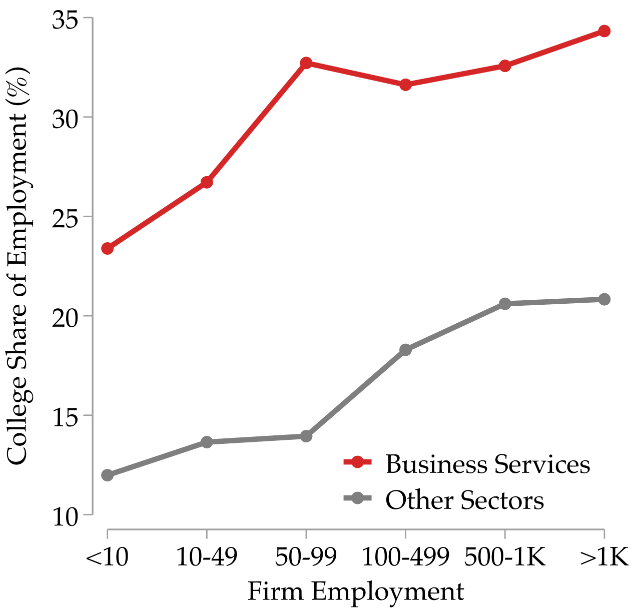
Notes: The figure shows employment and average wages over time for all 1-digit NAICS sectors in the US economy. The underlying data come from the Quarterly Census of Employment and Wages (QCEW). The left panel shows employment relative to 1980 in Business Services in red and all other 1-digit NAICS sectors in grey. The right panel shows average wages relative to 1980 in Business Services (red) and all other 1-digit NAICS sectors (grey).

FIGURE OA.13: INVESTMENT PRICE INDICES FOR EQUIPMENT CAPITAL AND INTELLECTUAL PROPERTY, 1980–2015



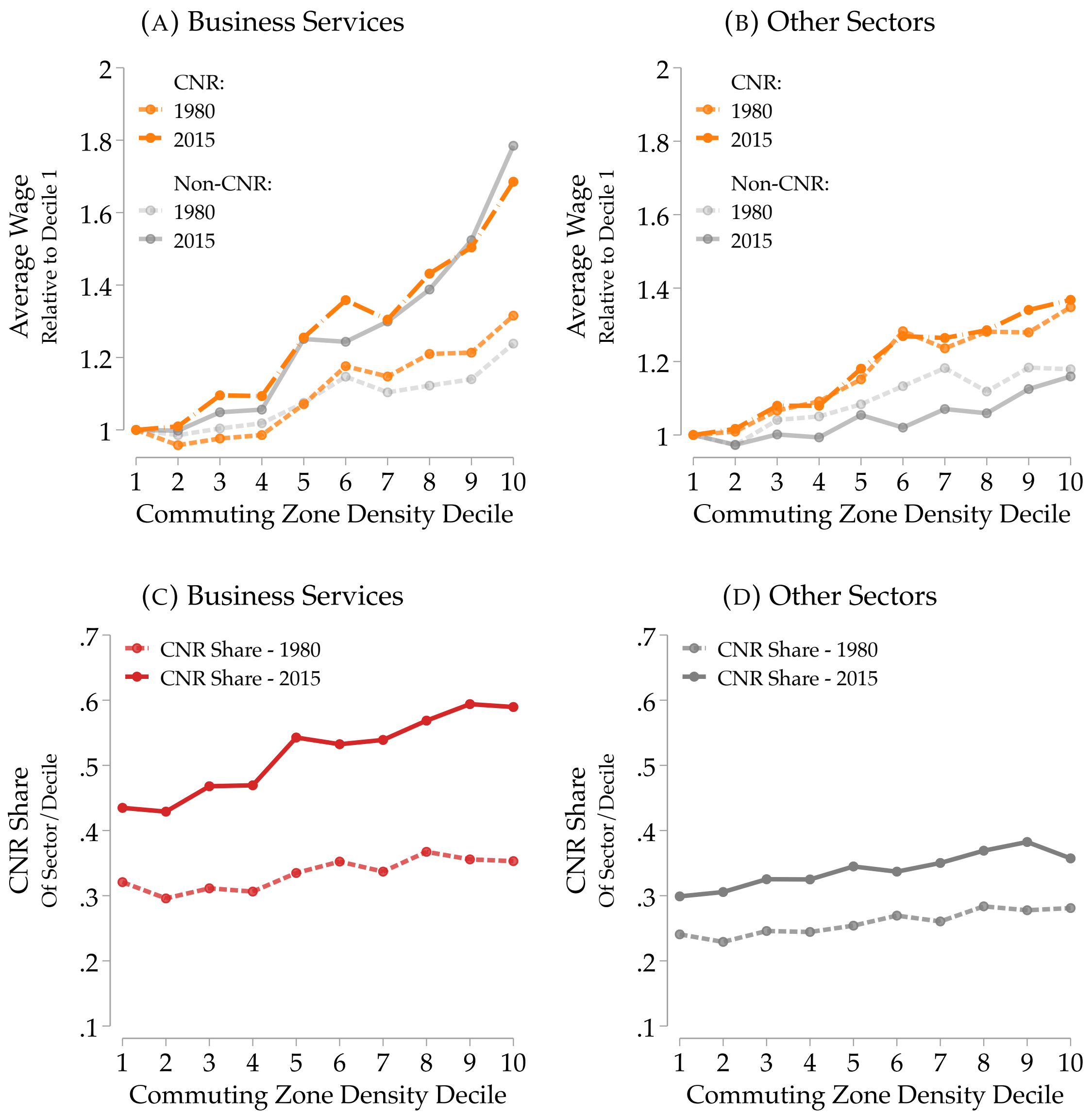
Notes: The figure shows investment prices for different types of capital between 1980 and 2015. The underlying data series come from the BEA asset price tables for 1980–2018. We show all price series relative to the BEA PCE deflator. The left panel shows the investment price series of equipment capital and its four subcomponents, and the right panel shows the investment price series of intellectual property and its three subcomponents.

FIGURE OA.14: EDUCATION AND FIRM SIZE, 1992



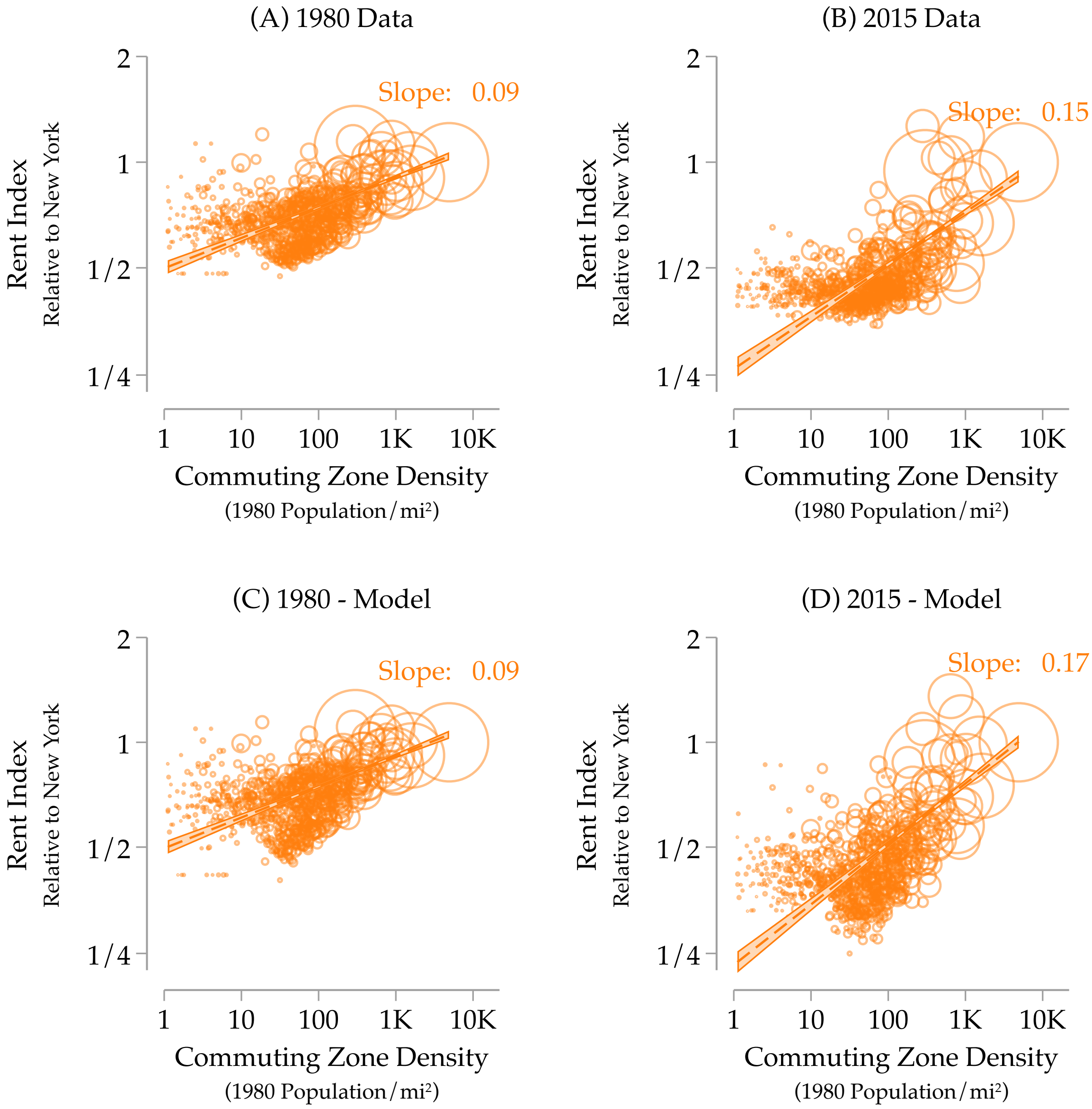
Notes: The figure shows how the college share of employment varies with firm size in Business Services and the rest of the economy in 1992. The underlying data come from the US Census 1992 Current Population Survey. We drop employees working more than 168 hours per week and part-time workers who worked less than 30 hours in a "usual" week. We classify workers with more than a bachelor's degree as "college-educated" and all other workers as "non-college." For each firm size bin, we compute total employment across all respondents and then show the fraction of these respondents with a college degree.

Figure OA.15: Cognitive Non-Routine Occupations and Urban-Biased Growth



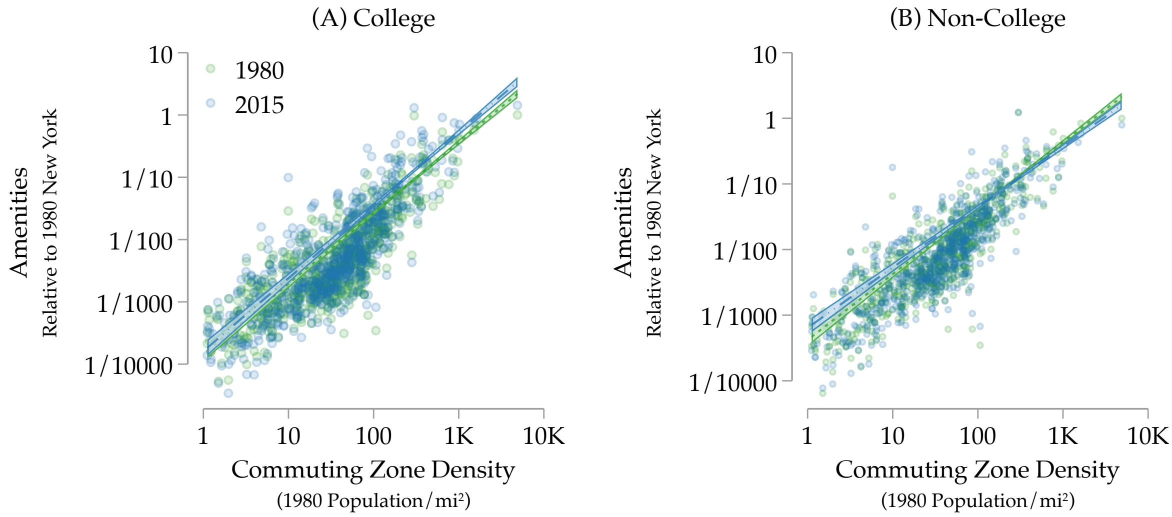
Notes: The figure uses data from the US Census files for 1980 and the ACS for 2015. We create ten groups of commuting zones increasing with population density, each accounting for 10% of 1980 employment. Panel A shows average wages among CNR and non-CNR workers across commuting zone deciles in 1980 and 2015 in Business Services. Panel B shows average wages among CNR and non-CNR workers across commuting zone deciles in 1980 and 2015 outside Business Services. Panel C shows CNR shares of employment within Business Services across commuting zone deciles in 1980 and 2015. Panel D shows CNR shares of employment outside Business Services across commuting zone deciles in 1980 and 2015.

FIGURE OA.16: RESIDENTIAL RENTS ACROSS COMMUTING ZONES, 1980 AND 2015



Notes: The figure shows a scatter plot of residential rent price indices against commuting zone density for 1980 and 2015 in the data and the IT-only economy. The 1980 data come from the US Decennial Census, and the 2015 data from the American Community Survey. We construct the rent price index as commuting-zone-year fixed effects in a regression of residential rents on housing characteristics. The model data comes from a counterfactual economy in which only the investment price of IT and the aggregate share of college workers change, as in the data. Panels A and B show data for 1980 and 2015; Panels C and D show rental indices in the model for 1980 and 2015. We show indices relative to the value of New York in that year. We show fitted lines with 95% confidence intervals. The size of a dot is proportional to the commuting zone population. Note that data and model coincide in 1980 by construction.

FIGURE OA.17: AMENITIES IN THE MODEL



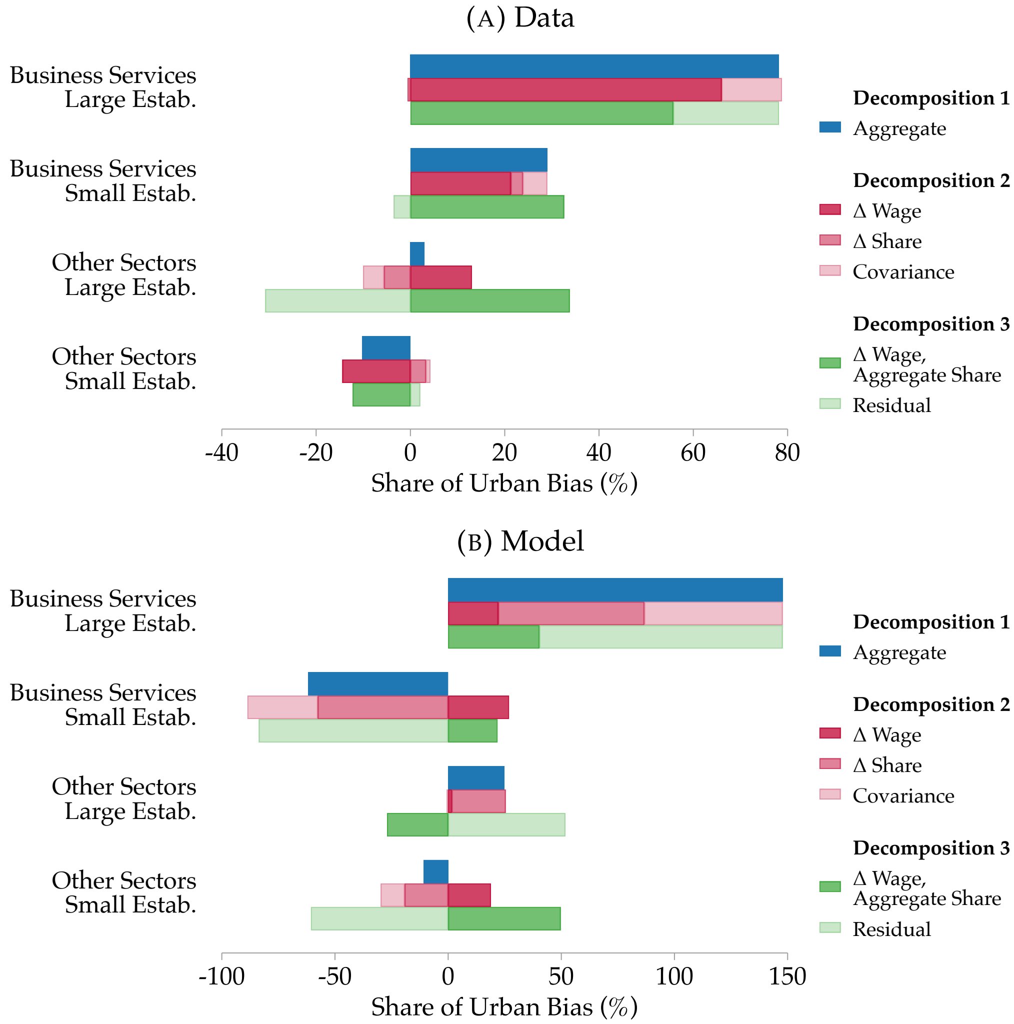
Notes: The figure shows the calibrated amenity residuals across commuting zones (Tolbert and Sizer, 1996) in 1980 and 2015, separately for each sector and education group. Each dot represents a commuting zone-, education-, and year-specific amenity term. The size of each dot is proportional to the commuting zone population. Amenities are normalized to 1 for New York in 1980 for each education group.

TABLE OA.3: REGRESSIONS OF IT EXPENDITURE PER EMPLOYEE ON FIRM SIZE, ALTERNATIVE BUSINESS SERVICES ASSIGNMENT

	Log IT Software/Worker	Log IT/Worker
	(1)	(2)
Log Sales	0.135	0.0782
	(0.00368)	(0.00326)
Business Services Share	0.111	0.145
	(0.0819)	(0.0778)
Business Services Share × Log Sales	0.0911	0.0774
	(0.00597)	(0.00543)
Fixed Effects		
NAICS-6 × Year	✓	✓
CZ × Business Services × Year	✓	✓
Firm Age	✓	✓
Observations (Approx.)	150,000	120,000

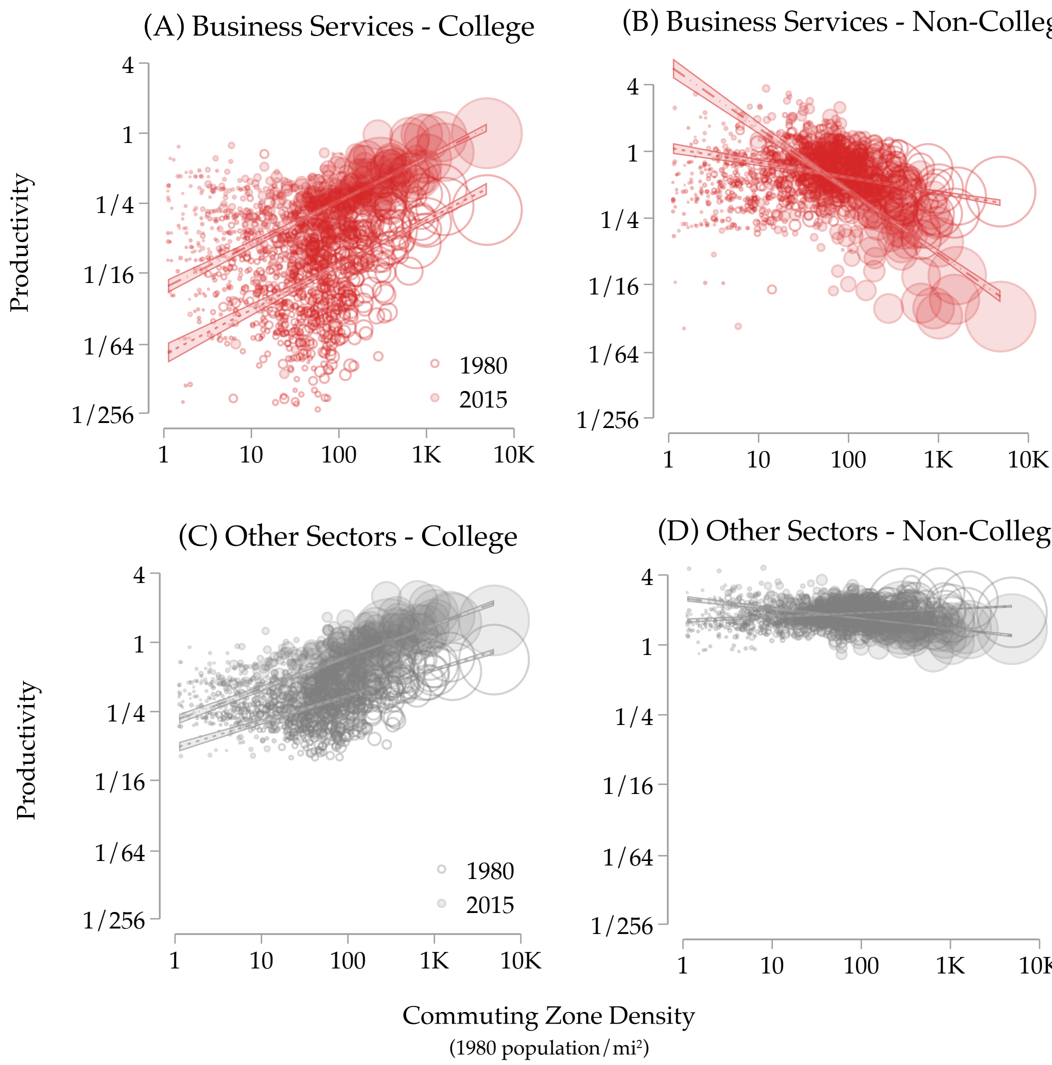
Notes: This table shows the regressions of IT capital expenditure payments per worker on firm sales. This is computed using BLS rental rates and a perpetual inventory method described in the text. This table replicates Table 1 with an alternative, continuous measure of whether a firm is in Business Services. In particular, we use the share of total employment at the firm in establishments with NAICS-5 industry codes, i.e., a firm's "Business Services Share." Column 1 uses firms in the ACES survey from 2006-2015. Column 2 uses firms in the ICTS survey from 2004-2013. All investment data converted to 2015 dollars.

FIGURE OA.18: URBAN-BIASED GROWTH AND ESTABLISHMENT SIZE IN MODEL AND DATA



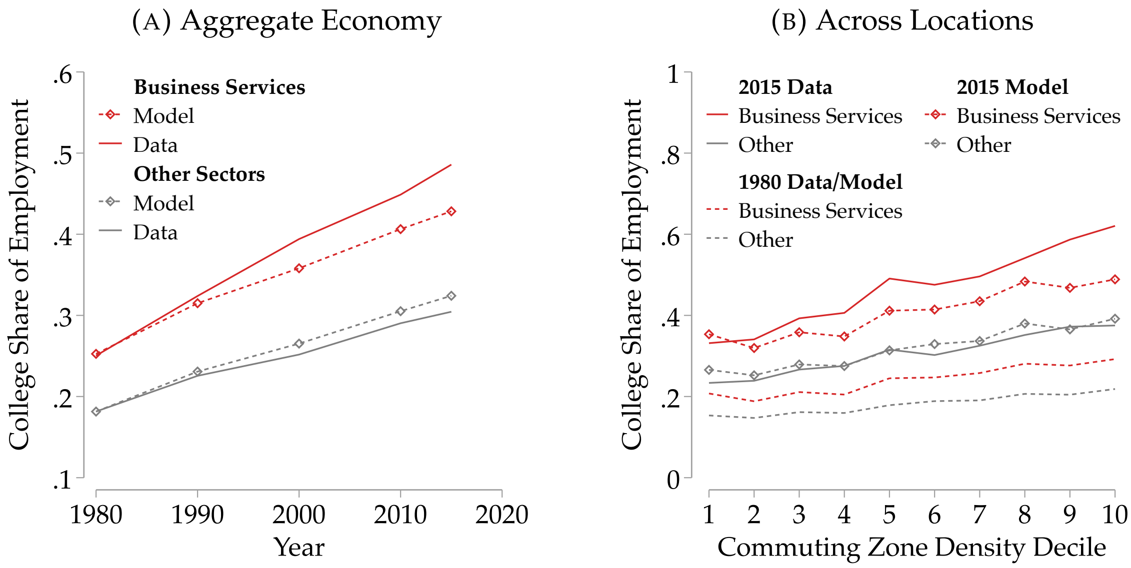
Notes: The figure decomposes the difference in 1980–2015 wage growth between commuting zones with above-median and below-median densities in 1980 into the contributions of large and small establishments within each NAICS 1-digit sector, separately in data and model output. The 1980 data come from the US Decennial Census, and the 2015 data from the American Community Survey. The model data comes from a counterfactual economy in which only the investment price of IT and the aggregate share of college workers change, as in the data. The blue bars show the share of the wage growth difference accounted for by each sector and establishment type (cf. equation (2)). The red bars decompose the blue bars into the separate contributions of within-industry wage growth, across industry relocation, and a covariance term (cf. equation (3)). The green bars decompose the blue bars into a component due to wage growth differences if all commuting zones had the same sectoral employment shares and a residual component (cf. equation (4)). We classify above-median density commuting zones as the highest density commuting zones jointly accounting for 50% of 1980 employment. We classify large establishments as the largest establishments jointly accounting for 50% of 1980 employment, leading to an employment cutoff for large firms of 108 employees. All values are adjusted for inflation to 2015 dollars using the BEA PCE price index.

FIGURE OA.19: PRODUCTIVITY BY SECTOR AND EDUCATION IN 1980 AND 2015



Notes: The figure shows the calibrated productivity residuals across commuting zones (Tolbert and Sizer, 1996) in 1980 and 2015, separately for each sector and education group. The size of each dot is proportional to the commuting zone population. We scale all productivity terms by the 2015 productivity of college-educated workers in Business Services in the New York commuting zone.

FIGURE OA.20: COLLEGE SHARES ACROSS LOCATIONS AND SECTORS IN MODEL AND DATA



Notes: The left panel shows the college share of employment in each sector over time for Business Services and the rest of the economy. The right panel shows the college share of employment within each commuting zone decile for Business Services and the rest of the economy in 1980 and 2015. Each decile accounts for one-tenth of the US population in 1980. The 1980–2010 data come from the US Decennial Census, and the 2015 data from the American Community Survey. The model data comes from a counterfactual economy in which only the investment price of IT and the aggregate share of college workers change, as in the data. The model matches aggregate college shares in the economy by construction.