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Universities, new tasks, and the rise of services

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Abstract
Structural transformation from manufacturing to services varies sharply across US regions. We document that regions with universities, especially highly ranked research institutions, experience faster growth in high-skill services, larger increases in the college wage premium, and a greater concentration of new work. We develop a task-based theory in which universities affect local economies by supplying college labor and adding new tasks. Our quantitative analysis shows that new tasks concentrated in top university regions account for a substantial part of regional differences in high-skill-service growth and the college wage premium increase between 1980 and 2015.

Keywords: structural transformation; skill premium; new task; economic geography
JEL codes: R10; O41; I25

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1 Introduction

Structural transformation from manufacturing to services is a central feature of the modern economy. While this transition has been extensively studied at the aggregate level, much less is known about how it unfolds unevenly across regions within a country. Among U.S. cities, Detroit and Pittsburgh, for example, entered the postwar period with similarly large manufacturing sectors, but their subsequent trajectories diverged. Detroit has struggled to adapt to the rise of services, while Pittsburgh has transformed into a hub for education, healthcare, and technology. What explains these regional differences in structural transformation from manufacturing to services?

One salient difference between the two cities is the presence of research universities. Pittsburgh is home to Carnegie Mellon University and the University of Pittsburgh, whereas Detroit lacks comparable institutions. As emphasized by Van Agtmael and Bakker (2016), Pittsburgh's transformation from a Rust Belt city to a "brain belt" hub illustrates how vibrant research universities can serve as engines of innovation, fostering new industries and expanding employment opportunities in high-value service sectors.[1]

This paper studies whether and how universities contribute to the local structural transformation from the traditional manufacturing to the modern service economy. Using data on U.S. commuting zones, we document that regions with universities, especially highly ranked research institutions, experienced faster growth in the employment share of high-skill services, larger increases in the college wage premium, and accounted for a disproportionate share of employment in newly emerging tasks. To interpret these patterns, we develop a task-based theory of local structural transformation. The model distinguishes three channels through which universities affect local labor markets: skilled labor supply, college-worker productivity, and the creation and adoption of new tasks. We extend the theory to a quantitative spatial model and assess the contribution of the new-task channel to regional structural transformation and the college wage premium.

We begin by documenting three empirical facts. First, regions with universities have seen faster growth in high-skill service employment. Between 1977 and 2016, the service employment share increased by 17.8 percentage points in commuting zones with a four-year college, compared

[1]In Van Agtmael and Bakker (2016) [p. 27], "Each brain belt is a tightly woven collaborative ecosystem of contributors, typically composed of research universities, community colleges, local government authorities, established companies with a thriving research function, and start-ups, usually supported by a variety of supporters and suppliers, including venture capitalists, lawyers, design firms, and others. These different types of entities establish their own unique identity as they share knowledge, interact, form a community, grow, and improve."

with 11.3 in those without one. Most of this difference reflects faster growth in high-skill services. Conditional on the initial employment size, sectoral composition, and population density, the relationship is more pronounced in regions hosting higher-ranked universities. In particular, commuting zones with a top 100 university experienced, on average, a nearly 5 percentage point larger increase in high-skill service employment share relative to those whose best institution ranks outside the top 440. University locations are not randomly assigned. To address this issue, we exploit the historical college site selection experiments. Comparing counties selected to host a university with unsuccessful finalist counties considered in the same siting process, we find that the two groups had similar sectoral composition in the 1970s, but diverged sharply thereafter. Winning counties experienced a larger decline in manufacturing employment share and larger increases in the aggregate and high-skill service employment shares. This suggests that universities themselves contributed to regional differences in the rise of services, rather than local characteristics associated with the presence of a university.

Second, the college wage premium increased more in regions with universities. Since the early 1990s, commuting zones hosting universities, especially highly ranked institutions, have consistently exhibited a higher college wage premium than regions without a university. This pattern remains robust after controlling for population density, pointing to a "university wage premium" distinct from the canonical urban wage premium. Thus, university regions experienced not only faster growth in skill-intensive services but also a larger increase in the relative wage of college workers.

Third, employment associated with newly emerging work is disproportionately concentrated in university regions. Combining national occupation-level data on new job titles from Autor et al. (2024) with local occupational employment from the Census and American Community Survey, we find that occupations with large new- title shares, such as computer systems analysts and software developers, are more prevalent in commuting zones with top universities. More generally, by constructing a "New Task Index," which approximates a measure of employment share in the new titles in each commuting zone, we find that the index is systematically higher in regions with universities, particularly top-ranked ones. This observation suggests that universities shape local labor markets not only by supplying skilled workers but also by facilitating the creation and adoption of new tasks.

Motivated by these stylized facts, we develop a task-based framework that links skills, tasks, and sectors. College and non-college workers differ in their comparative advantage across tasks, generating a simple task assignment rule: non-college workers specialize in lower-ranked tasks, such as cleaning and machine assembly, while college workers perform higher-ranked ones, such as management and research. Relative to manufacturing, high-skill services adopt a broader set of tasks, including frontier tasks. This sectoral asymmetry is motivated by existing studies showing that new tasks are more prevalent in high-skill services in the last four decades. In equilibrium, task assignment and the college wage premium are jointly determined by relative skill supply and the adopted task frontier.

We use the model to clarify the race between education and new tasks. An increase in college labor supply lowers the college wage premium and reallocates some incumbent tasks toward college workers. An expansion of the task frontier has the opposite wage effect. Newly adopted frontier tasks are performed by college workers, raising their relative demand and the college wage premium.[2] The resulting increase in the college wage premium reallocates some incumbent tasks toward non-college workers. Because non-college workers are less productive at the reassigned tasks, frontier expansion can increase service employment even when the nominal expenditure share of services is fixed. Task expansion can therefore raise the college wage premium and shift employment toward high-skill services simultaneously, consistent with our empirical facts.

To validate and quantify the importance of the new task channel, we embed the mechanisms in a quantitative spatial model with heterogeneous regions, worker mobility, and local housing markets. We use the model's equilibrium structure to recover local fundamentals that are not directly observed in the data. Manufacturing's college-to-non-college wage bill ratio identifies the task assignment threshold, and conditional on this threshold, the corresponding ratio in services identifies the task frontier. Then the relative productivity of college workers is identified by observed relative wages. And the remaining regional fundamentals are recovered from sectoral expenditures, prices, worker locations, and rents. We validate the recovered task frontier using the New Task Index, which does not enter our model estimation. We also show that both the recovered task frontier and the relative productivity of college workers grow more in regions with highly ranked universities. These relationships confirm the link between universities and task-frontier growth on top of the skill-biased productivity change.

Finally, we use the estimated model to quantify how much task expansion contributed to

[2]For example, leading U.S. universities in Silicon Valley and the Research Triangle have supplied large numbers of engineering and computer science graduates while also contributing to the emergence of new forms of work associated with artificial intelligence and digital platforms.

the structural transformation and the rise in college wage premium. Our baseline counterfactual sets the 2015 task frontier in commuting zones with a top-100 university back to their 1980 levels, while leaving them unchanged elsewhere. We then solve for counterfactual wages, task assignment, prices, and the spatial allocation of college workers. Task expansion accounts for approximately 32 percent of the observed increase in the value-added share and 19 percent of the increase in the employment share of high-skill services in top-university regions. Without task expansion, the college wage premium in top-university regions would have risen roughly four percent less. Importantly, these effects extend beyond the directly treated regions because changes in wages, migration, prices, and service demand propagate across regions. Through these spatial adjustments, we find slower growth in high-skill services even in regions without top universities and smaller dispersion in the college wage premium across regions.

Taken together, the results highlight the role of universities in shaping the regional differences in the rise of high-skill services and the college wage premium, primarily through the new-task channel.

This paper contributes to four strands of literature. First, we contribute to the literature on structural transformation. A large body of work explains the aggregate shift from agriculture to manufacturing and then to services through differences in sectoral productivity growth, non-homothetic demand, among others (e.g., Baumol 1967; Matsuyama 1992; Ngai and Pissarides 2007; Buera and Kaboski 2012; Comin, Lashkari, and Mestieri 2021). A related literature studies the geographic dimension of structural transformation at the sub-national level, emphasizing regional convergence, technology diffusion, comparative advantage, and worker mobility (e.g., Caselli and Coleman II 2001; Desmet and Rossi-Hansberg 2009, 2014; Eckert and Peters 2022; Takeda 2023). We provide new evidence on regional differences in the rise of high-skill services and develop a task-based mechanism through which universities shape this transformation.

Second, our theory relates to the literature on tasks, technological change and relative skill demand. We build on models in which workers sort across tasks according to comparative advantage (Grossman and Rossi-Hansberg, 2008; Acemoglu and Autor, 2011). This approach is motivated by evidence that new work is concentrated in cities initially abundant in college graduates (Lin, 2011) and that newly emerging tasks account for a substantial share of employment growth (Autor et al., 2024). Our new-task mechanism is also related to models of automation and new tasks (Acemoglu and Restrepo, 2018, 2022), with a focus on multiple sectors and locations. Our framework provides a task-based perspective for both skill-biased technical and structural change emphasized by Buera et al. (2022). In particular, task expansion provides a common source of the rise in college wage premium and employment growth in high-skill services.

Third, the paper contributes to research on the college wage premium. Existing work explains its evolution through changes in relative skill supply and demand (Katz and Murphy, 1992; Goldin and Katz, 2007; Acemoglu, 2003), and a related literature studies urban wage premia and differences in return to skill across cities (Glaeser and Maré, 2001; Gould, 2007; Baum-Snow and Pavan, 2012). We document that regional differences in college wage premium are systematically related to university presence and quality. Our model distinguishes the effects of college labor supply and relative college workers productivity from task expansion, which raises skill demand while also changing task assignment and sectoral employment.

Finally, we contribute to the literature on universities and regional development. Prior work documents the effects of universities on innovation, productivity, and local employment growth (Valero and Van Reenen, 2019; Hausman, 2022; Alon, Capelle, and Matsuda, 2022; Andrews, 2023; Howard, Weinstein, and Yang, 2024). Related research studies the local labor market effects of college expansion, and the broader relationship among human capital, innovation, and regional development (Carneiro, Liu, and Salvanes, 2023; Gennaioli et al., 2013; Gagliardi, Moretti, and Serafinelli, 2023; Akcigit, Pearce, and Prato, 2025). We add to this literature by showing that universities are associated not only with the supply and productivity of college workers, but also with the creation and local adoption of new tasks.

2 Data and Motivating Facts

2.1 Data

We briefly describe our dataset construction procedure with the details relegated to Appendix F. Our main geographical unit of analysis is the Commuting Zone (CZ), which is commonly used to define local labor markets.[3] Following Autor and Dorn (2013), we map all data to 1990 CZ boundaries. Appendix G shows that the results are similar using counties or metropolitan statistical areas.

Sectors. We primarily focus on manufacturing and services. As in Buera et al. (2022), we further distinguish between high- and low-skill activities within each sector. High-skill service sectors

[3] Moreover, ACS historical data are reported in different geographic units, such as County Groups and Public Use Micro Areas. To ensure consistency, we map all observations to a common geography, the 1990-based CZs, following Autor and Dorn (2013).

include finance, insurance and real estate (FIRE), business services, health services, legal services etc., and low-skill services include the remaining ones such as retail trade and personal services. Appendix F reports the complete sectoral classification.

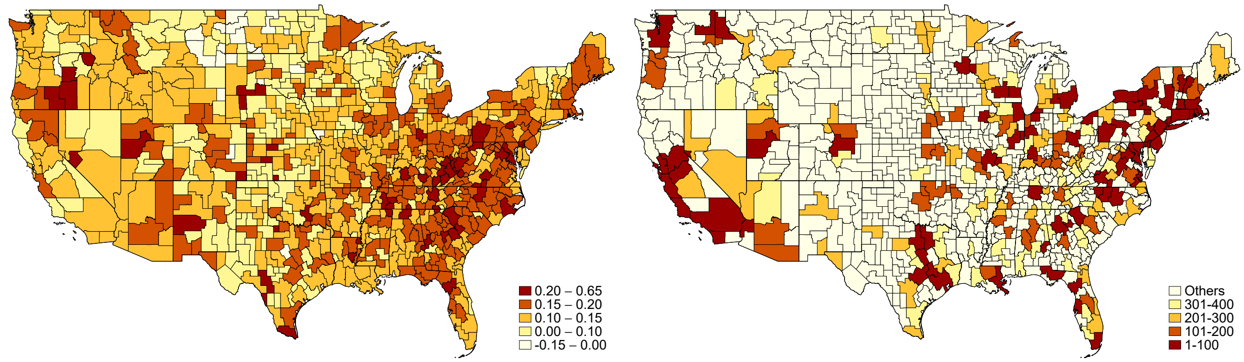
Local Labor Markets. Our dataset combines County Business Patterns (CBP) and the American Community Survey (ACS). CBP provides annual county-level employment and establishment counts by industry from 1977 to 2016. We aggregate these data to CZs and harmonize industry classification following Acemoglu et al. (2016). Since the CBP data do not include detailed micro-level information on wages or the occupational and skill composition of the workforce, we supplement it with individual survey data from the ACS, aggregated to the CZ level using the survey-provided individual weights. Our ACS dataset provides information on wage and employment by location, industry, occupation, and education attainment, for every decade since 1970 and annually since 2005. Throughout our analysis, we classify college graduates as *high-skilled labor*. Appendix Figure F.1 shows that employment measures and structural transformation trends from the ACS are broadly comparable to those from CBP.

New Tasks. ACS data report occupations but not job titles, and therefore do not directly capture the task content of each occupation. For example, we observe wages and employment for individuals classified as "Computer systems analysts," an occupation present in the Census since 1970. However, we do not observe more granular job titles such as "Artificial intelligence specialist," which was introduced only in 2000. To measure the geography of new tasks, we combine occupation-level employment data from the ACS with data on job titles underlying each occupation constructed by Autor et al. (2024). These data allow us to identify occupations experiencing rapid creation of new job titles and to construct a CZ-level measure of new tasks.

Universities. Data on universities are drawn from the Integrated Postsecondary Education Data System (IPEDS), which covers the universe of accredited U.S. higher education institutions from 1980 to 2022. Given our focus on the role of universities in generating high-skilled labor and facilitating task creation, we distinguish four-year colleges from other institutions. To proxy for institutional quality, we classify universities into five groups based on the 2016 *U.S. News & World Report* Best National Universities list.[4]

[4]Since historical rankings are not consistently available, we use the 2016 rankings as a proxy for institutional quality across the sample, given the relative stability of broad rank groupings despite annual fluctuations in individual positions. Our main results are also robust to alternative ranking lists (see Appendix G).

Figure 1: Geography of Structural Transformation and Colleges in US



(a) Change in Employment Share of High-Skill Services

(b) US Universities by Ranking

Notes: Panel (a) plots the change in high-skill service sector employment share between 1977 and 2016 across CZs, grouped into five bins based on the magnitude of this change. Panel (b) plots the distribution of colleges by their 2016 US News rankings. CZs in the US are divided into five groups by the ranking of the best university. Data source: US News Best National Universities Ranking and CBP.

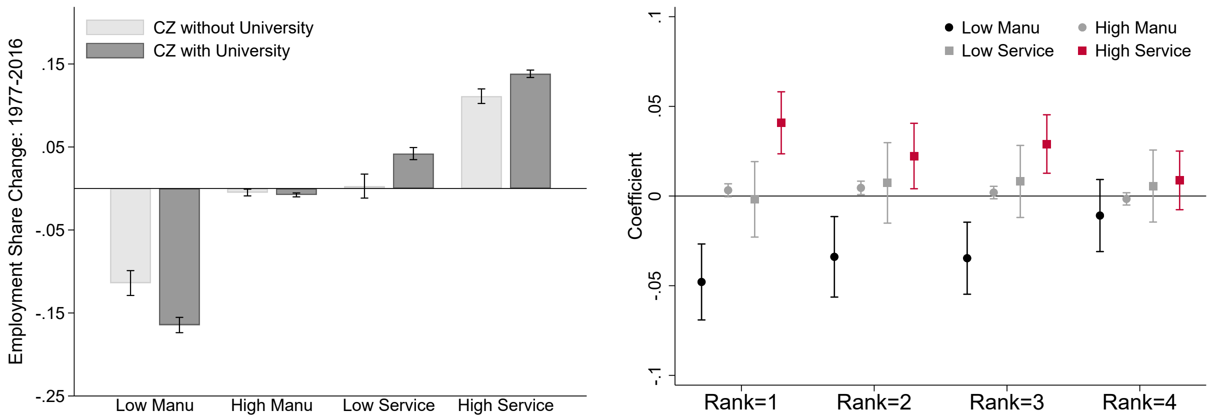
Merged Dataset. We merge the sectoral, labor market, task and university data, and harmonize across geographic units, industrial and occupational classifications using the crosswalks of Autor and Dorn (2013) and Autor, Dorn, and Hanson (2019).[5] The resulting panel dataset provides, for each CZ, information on industry composition, occupation, educational attainment, employment, wages, number of establishments, university presence, and university quality.

2.2 Motivating Evidence

Consistent with a large body of literature, both CBP and ACS data reveal clear patterns of aggregate structural transformation from manufacturing to services, particularly toward high-skill services. However, not all regions participated equally in the rise of high-skill services. Panel (a) in Figure 1 presents the substantial geographic variation in the growth of high-skill service employment between 1977 and 2016, with some regions experiencing gains exceeding 25 percentage points and others seeing more modest increases, and in some cases, declines. Panel (b) shows that top-ranked universities are unevenly distributed across regions and are not confined to large cities. These patterns raise a natural question: are universities related to the geography of structural transformation? We document three new facts that motivate our theoretical framework. Regions with universities, especially highly ranked institutions, experience faster growth in high-skill services, larger increases in the college wage premium, and a greater prevalence of

[5] In exercises that require the use of county-level data, such as the identification exercise in Fact 1, we use county-level CBP data.

Figure 2: Universities and Local Structural Transformation



(a) Average change in sectoral employment share in CZs with and without universities

(b) Change in sectoral employment share in CZs by university rankings

Notes: Panel (a) shows average changes in sectoral employment shares between 1977 and 2016 for CZs with and without a four-year university. Vertical lines represent 95 percent confidence intervals. Panel (b) shows coefficients from regressions of the change in each sector's employment share on indicators for the rank group of the highest-ranked university in the CZ. We group CZs by the presence of a university that falls into each ranking group: "1-100 (Rank=1)," "101-200 (Rank=2)," "201-300 (Rank=3)," and "301-440 (Rank=4)." The omitted group is "Others." In this regression, we control for log total employment, the sectoral employment share, and log population density in 1977. This figure plots the coefficients on these ranking indicators by sector, together with their 95 percent confidence intervals. Data sources are CBP, IPEDS, US Gazetteer Files, and the US News Best National Universities ranking.

newly emerging tasks.

Fact 1: Growth in high-skill service employment is more pronounced in CZs with universities, especially top-ranked ones.

We begin by investigating structural transformation across CZs by the presence of a four-year college. Panel (a) of Figure 2 reports the average change in sectoral employment shares between 1977 and 2016. Over this period, the aggregate service employment share increased by 17.8 percentage points in CZs with a university, compared with 11.3 percentage points in CZs without one. This difference is evident in both high- and low-skill service sectors; however, the expansion is driven primarily by high-skill services, whereas low-skill service shares changed much less, particularly in CZs without a university. The larger service expansion in university regions was accompanied by a larger decline in manufacturing, especially low-skill manufacturing.

The university gradient is strongest among highly ranked universities. Panel (b) of Figure 2 plots the estimated coefficients from regressions that compare CZs by the rank of their highest-ranked university. In the regression, we control for initial total employment, sectoral employment shares, and population density to absorb differences in initial size, industrial composition, and urbanization. Relative to the omitted category, CZs with higher-ranked universities, particularly those in the Top 300, exhibit larger increases in the high-skill service employment share and greater declines in low-skill manufacturing. By contrast, differences across rank groups in low-skill services and high-skill manufacturing are small. These findings suggest that the presence of a higher-ranked university is associated with a more pronounced shift from low-skill manufacturing toward high-skill services, even after controlling for initial employment levels and industrial composition.[6] Moreover, this relationship is concentrated among research institutions. Appendix Figure G.6 shows that the shift toward high-skill services is substantially larger around highly ranked research universities than around highly ranked liberal-arts colleges. This contrast suggests an important role of university research in accounting for these results.

College Site Selection. The cross-sectional comparisons do not establish that universities caused the subsequent structural transformation. Universities may have located in places that were more likely to grow, or their locations may be correlated with persistent local characteristics. To address this concern, we use the college site selection design of Andrews (2023) and Russell, Yu, and Andrews (2024), which compares counties selected to host a university with runners-up locations in the same siting process. The variation for identification comes from college location decisions made between 1839 and 1954. Given the winner and runners-up were considered within the same siting process, they were plausible alternatives for the same institution. We estimate the following equation:

$$\Delta \ell_c^j = \beta^j \,\text{Winner}_c + \gamma^j \,\mathbf{X}_c' + \delta_e^j + \epsilon_c^j, \tag{1}$$

where j denotes the sector and $\Delta \ell_c^j$ is the change in employment share for sector j in county c from 1977 to 2016. The indicator Winner_c takes a value of one if county c was selected to host a college and zero if it was a runner-up in the same site selection experiment. The vector of control variables $\mathbf{X}_c$ includes sectoral employment share, log total employment, and population density in 1977 at the county level. γ_e^j denotes experiment fixed effects, which restrict the comparison to counties considered in the same siting decision. A county can appear in more than one siting process, and it need not have the same status in each.[7] The experiment fixed effects accommodate such cases by defining treatment relative to each site selection decision. The identification

[6] One potential concern is that college-related employment may mechanically account for a large share of high-skill services in college towns. Appendix G shows that the results are similar when educational services are excluded.

[7] For example, Maricopa County was chosen as the site for Arizona State University but was not selected for the University of Arizona.

Table 1: Sectoral Employment Shares Changes: Winner versus Runner-Up Counties

	Manufacturing		Service		High-Skill Service	
	(1)	(2)	(3)	(4)	(5)	(6)
Winner County	-0.009^{**}	-0.021^{***}	0.011^{**}	0.021^{***}	0.007^{*}	0.016^{*}
	(0.004)	(0.007)	(0.005)	(0.007)	(0.004)	(0.008)

Notes: This table reports the estimates of β^j in equation (1). Columns (1), (3) and (5) include all colleges in Andrews (2023)'s sample. Columns (2), (4) and (6) restrict the sample to top 100 colleges only. Robust standard errors clustered by CZ are shown in parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

assumption is that, conditional on the fixed effects and controls, winning and runner-up counties would otherwise have experienced similar changes in sectoral employment changes.

Table 1 presents the estimates. Relative to runner-up counties, counties selected to host a university experienced a larger decline in the manufacturing employment share and a greater increase in the aggregate and high-skill service employment shares. Comparing Columns (2), (4) and (6) with (1), (3) and (5), we find that these differences are even more pronounced when the analysis is restricted to site selections involving universities that subsequently became top-ranked. These results echo the CZ-level evidence in Figure 2: establishing a university, especially a top one, is followed by a more pronounced shift from manufacturing toward high-skill services.

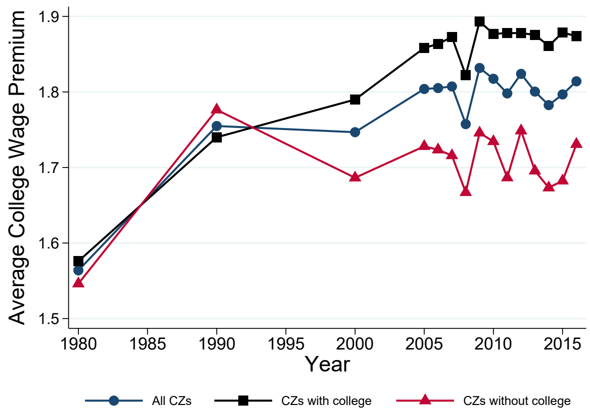
Fact 2: On average, the college wage premium increased more in CZs with universities, especially top-ranked ones.

Panel (a) of Figure 3 plots the average college wage premium between 1980 and 2016 for CZs with and without a four-year college. The series with circles, which represents the overall average across all CZs, increased steadily through 2005, before declining around the Great Recession and stabilizing thereafter, consistent with existing studies (e.g., Goldin and Katz, 2007).

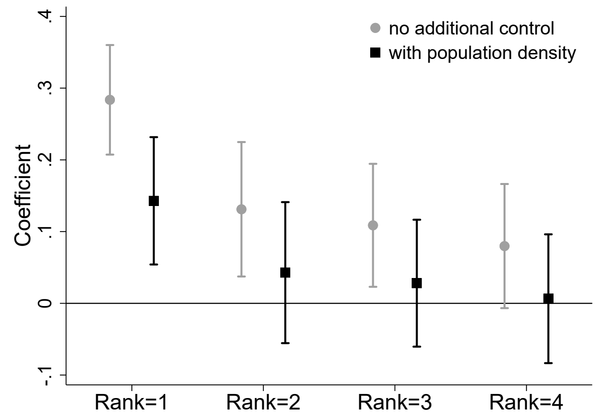
We extend this well-documented nationwide trend by disaggregating CZs based on the presence of a four-year college. In CZs with a university, the college wage premium exhibits a clear and persistent upward trajectory over the sample period. By contrast, CZs without a university followed a markedly different path. The premium increased initially at a pace comparable to—or even exceeding—that of CZs with a college but subsequently declined and, from 2000 onward, remained below that in CZs with a university. The national increase in the college wage premium was therefore accompanied by widening geographic differences in the returns to college workers.

The increase in the college wage premium is even larger in regions with higher-ranked uni-

Figure 3: Skill Premium Changes by Location



(a) Skill Premium in CZs with and without University



(b) Relative Skill Premium across CZs

Notes: Panel (a) plots the average college wage premium (skill premium) across all CZs, and separately for CZs with and without a four-year college, between 1980 and 2016. Panel (b) plots the coefficients and their 95 percent confidence intervals from regressions of the 1980–2016 change in the college wage premium on indicators for the rank group of the top university in each CZ. This figure reports specifications with no additional control and with log population density in 1980. Data sources are ACS, US Gazetteer Files and US News Best National Universities ranking.

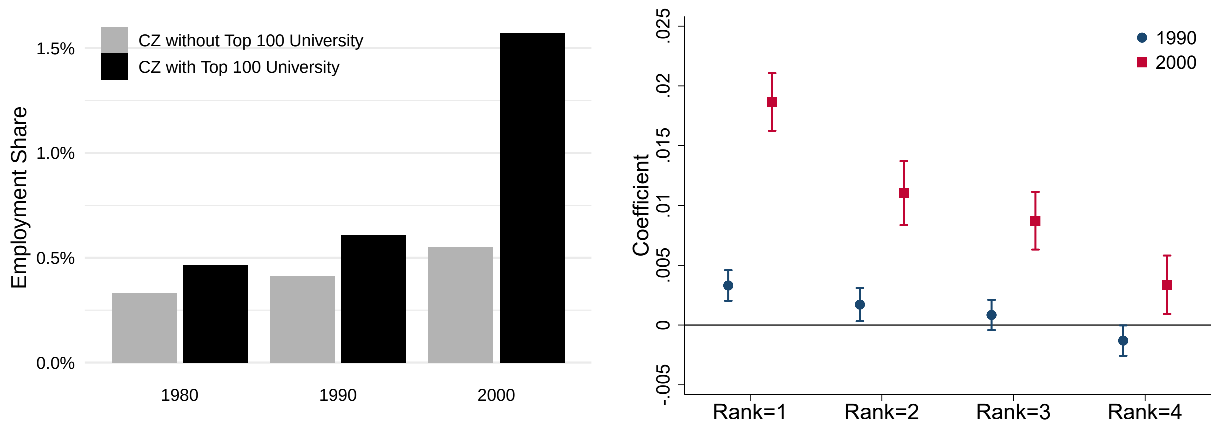
versities. Panel (b) shows that, between 1980 and 2016, CZs with a top-300 university experienced significantly larger increases in the skill premium than those with lower-ranked or no ranked institutions. The most pronounced increase is observed in CZs with top-100 universities, for which the estimated coefficient remains significantly positive after controlling for population density.[8] This pattern mirrors Fact 1. Regions with highly ranked universities experienced both faster growth in high-skill services and larger increases in the relative wage of college workers.

Fact 3: Employment in new tasks is concentrated in regions with top-ranked universities.

Autor et al. (2024) document that new work emerges in response to technological innovation. While their dataset reveals which occupations experience greater new-title creation, it does not provide employment counts at the title level or information on their geographic distribution. To address this limitation, we combine their "new title shares" for each occupation, which captures the relative intensity of new title creation within each occupation over time, with ACS occupational employment by location. The measures help to identify locations that specialize in occupations in which new job titles are prevalent. Figure 4 panel (a) illustrates employment

[8] We control for population density because wages and returns to skill vary systematically with urban scale and agglomeration (Glaeser and Maré, 2001; Gould, 2007; Baum-Snow and Pavan, 2012).

Figure 4: New Tasks by Location



(a) Employment Share in IT-Related Occupations

(b) New Task Index

Notes: Panel (a) plots employment share in IT-related occupations in 1980, 1990, and 2000. IT-related occupations include computer system analysts and computer scientists, and computer software developers. Panel (b) shows coefficients from regressions of the New Task Index defined in (2) on indicators for the rank group of the top university in each CZ, controlling for log population density. Vertical lines report 95 percent confidence intervals. Data sources are ACS, Autor et al. (2024) and US News Best National Universities ranking.

shares in IT-related occupations, including "computer system analysts and computer scientists" and "computer software developers." These occupations rank among the highest in terms of new title shares, reflecting the rapid expansion of the IT sector during the 1980s and 1990s. Their employment shares were substantially larger in CZs with a top university, suggesting that occupations with the most rapid expansion in new job titles are disproportionately concentrated in areas with strong higher education presence.

As an alternative piece of evidence, we propose a New-Task Index:

$$\text{New Task}_{it} = \sum_{o} \frac{L_{iot}}{L_{it}} \frac{N_{ot}^{\text{New}}}{N_{ot}}, \tag{2}$$

where L_{iot}/L_{it} represents the share of employment in occupation o at location i, and $N_{ot}^{\text{New}}/N_{ot}$ captures the new titles share within each occupation o in year t. This index is an approximate measure of the share of employment in these new titles by region and year. Conceptually, a location that has many occupations with both high employment share and high new titles share is where employment in new tasks is concentrated.[9] Our goal is to show whether this index varies with the existence of a (top) university in that region. To do so, we regress the index on indicators for the rank of the highest-ranked university in each CZ, controlling for population density.

[9]The occupation-level new title share is common across CZs within a year. Therefore cross-sectional variation in the index comes from differences in local occupational employment shares.

Panel (b) of Figure 4 shows the coefficients on these rank indicators for 1990 and 2000. CZs with top-ranked universities are associated with significantly higher concentration of new tasks, and the difference across regions has dramatically increased over time, suggesting a widening gap across regions in the concentration of new task employment. These observations motivate a task-creation role of universities, which we formalize in the subsequent sections.

3 A Task-Based Theory of Structural Transformation

We present a simple task-based model to study how universities shape local structural transformation. Universities affect local economies through two margins: the supply of college workers and the creation of new tasks. We characterize the equilibrium, derive the comparative statics, and show how task creation links the rise of high-skill services to changes in the college wage premium.

3.1 Setup

The economy consists of non-college workers, ℓ, and college workers, c, with population L_ℓ and L_c, where $L_\ell + L_c = 1$. Labor is supplies inelastically and earns competitive wages w_ℓ and w_c. Motivated by the empirical evidence that both the rise of services and its regional variation are concentrated in high-skill services, we focus on two sectors: high-skill services and the rest, which we call manufacturing. Workers of both types have Cobb-Douglas preferences, spending a share α of income on services and $1 - \alpha$ on manufacturing goods.[10]

Tasks Performed by Individuals. Tasks are horizontally differentiated, for example, car assembly, weaving textiles, constructing housing, and AI research.[11] They are indexed by $j \in [0, J]$, where J denotes the upper bound of the set of existing tasks. This set of tasks expands as new tasks are introduced in the economy. Without loss of generality, we assume $J > 1$. Production of these tasks only requires labor: one unit of labor provided by type i worker produces z_{ij} units of task j. Tasks are ordered so that the relative productivity of non-college workers, $z_{\ell j}/z_{cj}$, is strictly decreasing with the task index j. This implies that college workers have a comparative

[10]Cobb–Douglas preferences hold sectoral expenditure shares fixed and abstract from income effects under non-homothetic demand preferences (Buera and Kaboski 2012; Comin, Lashkari, and Mestieri 2021). In our baseline model, structural transformation arises instead from changes in production organization at the task level. Non-homothetic demand would reinforce this mechanism, since task-frontier expansion raises income through higher skill premia and would therefore increase service demand.

[11]This setup is closely related to the classical Ricardian model (Dornbusch, Fischer, and Samuelson 1977) and the task assignment model in labor markets (Acemoglu and Autor 2011).

advantage in higher-indexed tasks. We assume that non-college workers can perform tasks below one but not tasks beyond the boundary.[12] The market for tasks is perfectly competitive. Unit production cost of task j by type i worker is: $\gamma_{ij} = w_i/z_{ij}$. Therefore, task j is performed only by non-college workers if:

$$\omega \equiv \frac{w_\ell}{w_c} \leq \frac{z_{\ell j}}{z_{cj}}, \tag{3}$$

where ω is the inverse college wage premium. This condition implies a task assignment rule: lower j tasks are taken by non-college workers and higher ones are performed by college graduates. Then, the price of each task is given by

$$\gamma_j \equiv \min\{\gamma_{cj},\ \gamma_{\ell j}\} \tag{4}$$

Manufacturing Firms. Manufacturing uses a fixed set of tasks $j \in [0,1]$ that enter symmetrically into production. We treat manufacturing as the benchmark sector and focus on how technological expansion occurs through the creation of new tasks in high-skill services. The manufacturing production technology is, for simplicity, assumed to be Cobb-Douglas: $q^M = \exp\left[\int_0^1 \log \tau_j \, dj\right]$, where τ_j is the input of task j. Since manufacturing goods are freely traded with the large economy, we normalize the unit cost and price of manufacturing, so that $p^M = 1$.

Service Firms. In contrast to manufacturing, service production uses tasks on the interval $j \in [0, J]$, where J denotes the adopted task frontier. The key sectoral asymmetry in the model concerns the task set. Manufacturing uses a fixed set of tasks, whereas high-skill services can expand through the adoption of additional tasks. This assumption reflects the idea suggested by our empirical evidence: universities are associated with the expansion of specialized tasks in IT services.[13] Given the frontier, service output, q^S, is:

$$q^S = \min_{j \in [0,J]} \left\{\varphi_j \tau_j\right\} \tag{5}$$

where τ_j refers to input of task j, and φ_j denotes its effectiveness in service production. The production technology exhibits that all tasks are essential. Intuitively, an asset management firm in the service sector requires both simple tasks (e.g., cleaning, driving) and more skill-intensive

[12]Formally, we assume that $z_{\ell j} > 0$ for $j < 1$, $z_{cj} > 0$ for all $j \in \mathbb{R}_+$, $\lim_{j \uparrow 1} \frac{z_{\ell j}}{z_{cj}} = 0$, and $z_{\ell j} = 0$ for $j \geq 1$. This simplifies the characterization of the task threshold. More generally, we require only that college workers have a sufficiently strong comparative advantage in performing most complex tasks.

[13]The fixed manufacturing task set is a modeling assumption, not a claim that manufacturing never develops new tasks. If task frontiers expanded in both sectors, their relative expansion would be the relevant object. We hold the manufacturing frontier fixed to isolate the role of service-related task expansion.

ones (e.g., market analysis, fund management). A shortfall in any one task limits output; that is, tasks are weak links as in Jones and Tonetti (2026).

The task frontier is determined before production. We do not model the creation and adoption decisions explicitly, but summarize the adopted frontier by:

$$J = \mathcal{J}(u), \qquad \mathcal{J}'(u) > 0, \tag{6}$$

where u denotes task-creation and adoption capacity, which captures local fundamentals such as universities or innovation capacity. The reduced-form relationship (6) may reflect either the local availability of new tasks or the cost of implementing them. Universities may affect both margins, although our analysis does not distinguish between them. We take J as given and study how its expansion affects task assignment, labor demand, and wages.[14] Section 4.2 and Appendix C provide further discussions.

Producing one unit of services requires $1/\varphi_j$ units of each adopted task. Under perfect competition, the service price equals unit cost:

$$p^S = \int_0^J \frac{\gamma_j}{\varphi_j}\, dj \tag{7}$$

Labor Market Clearing. The total expenditure equals aggregate income: $X = w_\ell L_\ell + w_c L_c$. We focus on the case $j^* < 1$, so that manufacturing uses both non-college and college graduates. The labor market clearing condition states that labor supply and demand are equal for each type i. We start with labor market clearing condition for college graduates, which requires that total payments to college graduates equal the sum of payments to those employed in the production of tasks used in services and manufacturing:

$$w_c L_c = \left[\alpha\lambda(j^*, \omega, J) + (1-\alpha)\left(1 - j^*\right)\right] X, \tag{8}$$

where

$$\lambda(j^*, \omega, J) \equiv \frac{\int_{j^*}^{J} \left(\gamma_j/\varphi_j\right) dj}{\int_0^J \left(\gamma_j/\varphi_j\right) dj} \tag{9}$$

In equation (8), the right-hand side represents demand for tasks performed by college workers. The first term corresponds to demand from service firms: total expenditure on services is αX, and

[14] One possible microfoundation is introducing productivity gains from broader tasks: $q^S = A(J)\min_{j\in[0,J]}\{\varphi_j \tau_j\}$, with $A'(J) > 0$, as in Benassy (1998). If the marginal benefit of a broader task menu exceeds the marginal cost of adding frontier tasks over the feasible range, firms adopt the locally available frontier. Our baseline framework does not rely on this particular specification or impose a direct relationship between J and measured service productivity.

$\lambda(j^*, \omega, J)$ denotes the share of service production costs accruing to tasks performed by college workers. The second component captures demand from the manufacturing sector. Total expenditure on manufacturing goods is $(1-\alpha)X$, and $1-j^*$ denotes the share of manufacturing tasks performed by college workers.

The labor market clearing condition for non-college workers is:

$$w_\ell L_\ell = \left[\alpha\big(1-\lambda(j^*, \omega, J)\big) + (1-\alpha)\, j^*\right] X, \tag{10}$$

where the right-hand side combines the payments to non-college workers performing tasks used in the services and manufacturing sectors.

3.2 Equilibrium

We now formally define the equilibrium for this economy as follows. Given the relative supply of college and non-college workers, L_c/L_ℓ, and the adopted task frontier J, an equilibrium is characterized by a relative wage $\omega \equiv w_\ell/w_c$ and a task threshold j^* that solve labor market clearing conditions given by equations (8) and (10), and condition (3) with equality.

Combining equations (8) and (10) yields:

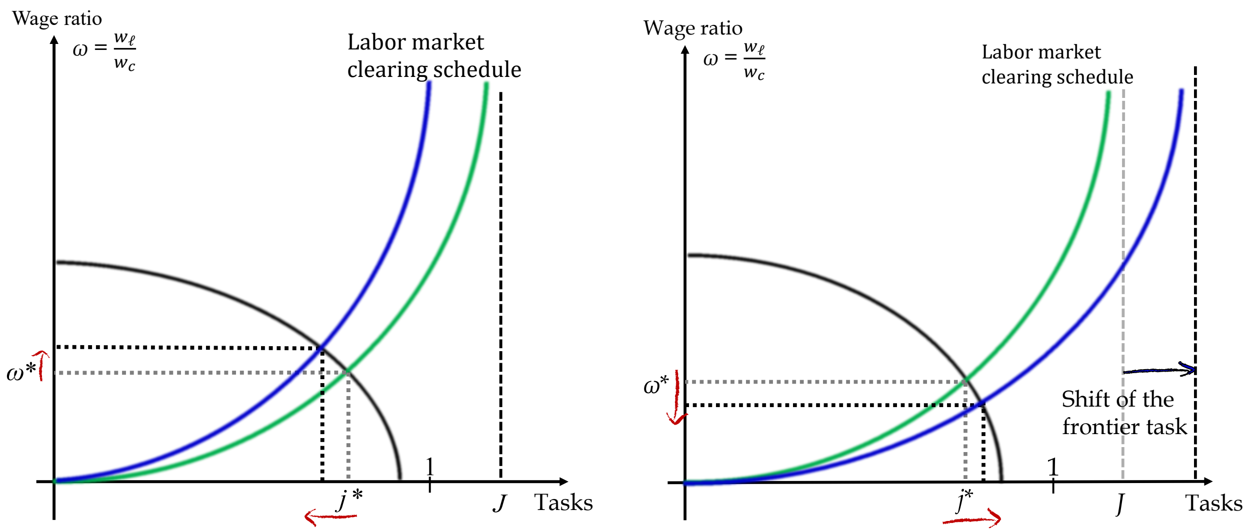
$$\omega \equiv \frac{w_\ell}{w_c} = \frac{\alpha\left[1-\lambda(j^*, \omega, J)\right] + (1-\alpha) j^*}{\alpha\lambda(j^*, \omega, J) + (1-\alpha)\big(1-j^*\big)} \frac{L_c}{L_\ell} \equiv \Gamma\left(j^*, \frac{L_c}{L_\ell}, J\right), \tag{11}$$

Equation (11) defines the wage ratio of non-college to college graduates. For a given task threshold j^*, it determines the relative wage required to clear the demand and supply of each type of worker. A higher j^* assigns a larger share of tasks to non-college workers and therefore requires a higher relative non-college wage to clear the labor market. The labor market clearing schedule, $\Gamma(j^*, L_c/L_\ell, J)$, is increasing in j^* and $\lim_{j \to J} \Gamma(j, \frac{L_c}{L_\ell}, J) = \infty$. Since the right-hand side of (3) is decreasing in j, the task threshold j^* and wage ratio ω are uniquely determined as the intersection of these two curves.

Proposition 1 (Equilibrium). *For any finite number of $L_\ell > 0$, $L_c > 0$ and a finite task frontier J, there exists a unique equilibrium (j^*, ω) solving equations (3) and (11).*

See Appendix A for the proof. We next use these equilibrium conditions to investigate the responses of the wage ratio, which is the inverse college wage premium, and task assignment to changes in the primitives of this economy.

Figure 5: Supply of High-Skilled Labor and Innovation of Tasks



(a) Supply of High-Skilled Labor **(b)** Innovation and Adoption

3.3 Comparative Statics: Education and Task Creation

Universities can affect local labor markets through two distinct margins: the supply of college workers and the creation of new tasks. These margins have different implications for the college wage premium and task allocation. First, let us consider an increase in the relative supply of college workers, L_c/L_ℓ, holding the task frontier fixed. As illustrated by Panel (a) of Figure 5, the labor market clearing schedule shifts upward, increasing the relative wage $\omega = w_\ell/w_c$, that is, lowering the college wage premium. The lower relative cost of college labor shifts the task threshold j^* to the left, and therefore college workers perform a larger set of incumbent tasks. In other words, an expansion in education alone leads to task downgrading for college workers and exert downward pressure on the skill premium.

We next consider an expansion of the task frontier J, holding relative labor supply fixed. In the model, task creation is captured by an outward shift of the task frontier. The new tasks are performed by college workers, increasing the relative demand for college labor. As a result, this shift increases the college wage premium. Meanwhile, some incumbent tasks previously performed by college workers are reallocated to non-college workers, i.e., a rightward shift in j^*. Thus, task creation simultaneously raises the college wage premium and increases task complexity for non-college workers. Panel (b) of Figure 5 illustrates this adjustment. These effects are summarized in the following proposition:

Proposition 2 (Education and Task Creation). *Consider an equilibrium with endogenous task as-*

signment. Then, we can show:

i) An increase in the relative supply of college graduates, holding the task frontier fixed, reallocates tasks toward college workers and reduces the college wage premium.

ii) Skill-biased task creation that expands the task frontier increases demand for college labor, raises the college wage premium, and reallocates inframarginal tasks toward non-college workers.

A formal proof of this proposition is provided in Appendix A. Proposition 2 highlights a race between education and task creation. Education increases the relative supply of college labor and tends to compress the college wage premium. Task creation increases relative demand for college labor and the college wage premium. This contrast suggests that the task-creation channel dominates to rationalize the facts documented in Section 2.2. As such, we focus on the channel in the next subsection.[15]

3.4 *New Tasks and the Rise of Services*

We now show how task creation expands service employment. The mechanism does not operate through changes in sectoral expenditure shares. Instead, new tasks alter task assignment and relative wages, changing the labor required to produce services and thereby reallocating workers across sectors. Given the equilibrium task threshold j^*, labor employed in service is:

$$L^S = q^S \left[\int_0^{j^*} \frac{1}{\varphi_j z_{\ell j}} \, dj + \int_{j^*}^{J} \frac{1}{\varphi_j z_{cj}} \, dj \right], \tag{12}$$

Totally differentiating (12) with respect to the task frontier J yields

$$\frac{dL^S}{dJ} = \underbrace{\frac{q^S}{\varphi_J z_{cJ}}}_{\text{New frontier task}} \underbrace{+ q^S \left(\frac{1}{\varphi_{j^*} z_{\ell j^*}} - \frac{1}{\varphi_{j^*} z_{cj^*}} \right) \frac{dj^*}{dJ}}_{\text{Reassignment of incumbent tasks}} + \underbrace{\frac{dq^S}{dJ} \frac{L^S}{q^S}}_{\text{Output scale}} . \tag{13}$$

Equation (13) decomposes the employment effect into three components. First, when a new task is introduced at the frontier, it must be produced and used in service production. Because college workers have comparative advantage at the frontier, each new task directly raises employment in services. Second, task creation changes the assignment of incumbent tasks. The increase

[15] The model also allows for changes in college workers' relative productivity across existing tasks. An inward shift in $z_{cj}/z_{\ell j}$ strengthens college workers' comparative advantage, reallocates tasks toward college workers and raises the college wage premium. This channel differs from task creation, with opposite implications for j^* changes. The quantitative model estimates these two sources of task reallocation separately.

in college labor demand raises the college wage premium and shifts j^* to the right. Some tasks previously performed by college workers are therefore reassigned to non-college workers. At the threshold, cost minimization implies: $\frac{1}{\varphi_{j^*} z_{\ell j^*}} = \frac{1}{\omega} \frac{1}{\varphi_{j^*} z_{cj^*}}$ with $\omega < 1$. Because non-college workers are less productive in these tasks, the reallocation raises labor requirements per unit of service output. Third, task creation changes service output via its impact on service prices, which can be ambiguous. On the one hand, a broader task set incurs additional cost; on the other hand, changes in wages and task assignment alter the costs of incumbent tasks. Next, we establish the necessary and sufficient condition for the employment share of the service sector to grow.

Proposition 3 (**Task Expansion and Service Employment**). *Define the labor requirement of the frontier and threshold tasks as*

$$e_{cJ} \equiv \frac{1}{\varphi_J z_{cJ}}, \qquad e_{cj^*} \equiv \frac{1}{\varphi_{j^*} z_{cj^*}},$$

and let $\mathbb{A}^S = q^S/L^S$ and $\eta_Q \equiv \frac{d \log q^S}{dJ}$. Following an expansion of the task frontier J, service employment increases if and only if:

$$\mathbb{A}^S \left[e_{cJ} + e_{cj^*} (\omega^{-1} - 1) \frac{dj^*}{dJ} \right] + \eta_Q \; > \; 0. \tag{14}$$

The proposition summarizes the conditions under which task creation increases service employment. The first term in (14) is the labor required to perform the new frontier task. The second captures the additional labor required when incumbent tasks are reassigned from college to non-college workers. Both effects increase labor demand because $dj^*/dJ > 0$ and $\omega < 1$. The last term, η_Q, captures the potentially offsetting response of service output. Taken together, service employment therefore rises whenever the labor absorbed by new and reassigned tasks exceeds any contraction in service output. Since total labor supply is fixed and there are only two sectors, the corresponding increase in service employment is matched by a decline in manufacturing employment.[16]

The same mechanism can be seen from sectoral wage bills. Service employment can equivalently be written as

$$L^S = \left[\frac{\lambda(j^*, \omega, J)}{w_c} + \frac{1 - \lambda(j^*, \omega, J)}{w_\ell} \right] \alpha X, \tag{15}$$

[16] As discussed in the footnote 14 of Section 3.1, a broader task set may also raise service productivity. In this case the left-hand side of equation (14) includes an additional term $-\eta_A \equiv -\frac{d \log A(J)}{dJ}$. The productivity gain reduces the task inputs required per unit of service output and therefore offsets the labor-absorbing effects of task creation and reassignment. Our baseline theory abstracts from this direct productivity effect, whereas Section 6.2 examines it quantitatively.

where $\lambda(j^*, \omega, J)$ is the cost share of service tasks performed by college workers. Task-frontier expansion has offsetting effects on λ. New tasks tend to raise the college labor share, while the resulting wage adjustment reallocates some incumbent tasks toward non-college workers. Although the net change in λ is ambiguous, this task reassignment raises employment per dollar of service expenditure because $w_\ell < w_c$. Services can therefore absorb more labor even though nominal service expenditure remains fixed at αX.

3.5 The Roles of Universities

Our model points to three channels through which universities affect local labor markets: skilled labor supply, task creation, and college workers' productivity. These channels have different implications for task assignment, the college wage premium, and structural transformation.

Skilled Labor Supply. Universities increase the relative supply of college-educated workers. Holding the task frontier fixed, Proposition 2(i) implies that a higher L_c/L_ℓ lowers the college wage premium and reallocates tasks toward college workers. Since these workers require less labor to perform a given task, service employment per unit of output falls. The supply channel alone is therefore difficult to reconcile with the joint rise in high-skill service employment and the college wage premia documented in Facts 1 and 2.

Task Creation. Universities may facilitate the creation and local adoption of new tasks. Proposition 2(ii) shows that an expansion of the task frontier increases demand for college labor and raises the college wage premium. The resulting wage adjustment reallocates some incumbent tasks toward non-college workers. Proposition 3 further shows that service employment increases when the labor absorbed by new and reassigned tasks exceeds any contraction in service output. This mechanism is consistent with all three empirical facts: university regions account for a larger share of new tasks, experience faster growth in high-skill services, and exhibit larger increases in the college wage premium.

College Workers' Productivity. Universities may also raise college workers' productivity. This is the conventional skill-biased technical change channel different from the task creation mechanism emphasized in this paper. While also raising the relative wage of college workers, an increase in $z_{cj}/z_{\ell j}$ strengthens college workers' comparative advantage and reallocates incumbent tasks toward them. Unlike task creation, however, higher productivity does not expand the set of tasks used in production. In the quantitative model, we allow for both relative productivity changes and task creation.

Taken together, the empirical evidence is difficult to reconcile with changes in college labor supply alone and instead points to an important role for task creation. Changes in the relative productivity of college workers may also contribute, particularly to the rise in the college wage premium. Sections 4-6 quantify the contribution of these channels.

3.6 Discussion: Structural Transformation and Skill Premium

Our key mechanism is the expansion of the task frontier, which reshapes the assignment of existing tasks, affects sectoral labor demand and changes relative wages. This section discusses how our framework is related to but different from leading explanations of structural transformation and wage inequality.

Relative Prices and Measured Productivity. Standard models often attribute structural transformation to differences in sectoral productivity growth that change relative prices, which often assumes exogenous sectoral productivity differences. In our model, relative prices and measured productivity are endogenous to task composition. Expanding the task frontier introduces new tasks and changes the assignment of existing tasks, affecting production costs in both sectors. Consequently, changes in relative prices and measured productivity arise as equilibrium outcomes of task creation and task reallocation, even when task-level technologies remain unchanged. Appendix B.4 discusses the details.

Skill-Biased Technical Change. Existing explanations of the college wage premium differ primarily in the source of relative skill demand. In Katz and Murphy (1992), it is captured by a reduced-form demand shifter. In Buera et al. (2022), it rises because economic activity reallocates toward skill-intensive sectors. Our framework provides a task-based microfoundation for both mechanisms. The key primitive is the expansion of the task frontier. New tasks are disproportionately performed by college workers, increasing the demand for skill, while the resulting wage adjustment changes the assignment of incumbent tasks. As sectors that benefit most from frontier tasks expand, economic activity shifts toward high-skill services. Task-frontier expansion therefore links the rise in the college wage premium to changes in sectoral skill intensity and structural transformation. Appendices B.1 and B.2 provide the formal comparison.

Task-Based Technological Change. Our framework follows the task-based approach of Acemoglu and Restrepo (2020), in which technological change affects wages by changing the set of tasks assigned to different factors. Their framework allows for both automation, which transfers tasks from labor to capital, and new-task creation, which expands the productive domain of labor. Our focus is different. Our empirical evidence links universities, new tasks and the rise of high-skill services. We therefore abstract from automation and model technological change as an expansion of the task frontier. Because college workers have comparative advantage in frontier tasks, an increase in J creates new skill-intensive activities and raises relative skill demand. The resulting wage adjustment then reallocates incumbent tasks across worker types. Embedding this mechanism in a two-sector economy links task creation not only to the college wage premium, but also to the expansion of high-skill services. Appendix B.3 provides more details of this comparison.

4 A Quantitative Model of Local Structural Transformation

In this section, we embed the task-based framework in a quantitative spatial model with heterogeneous regions and worker mobility. This allows us to measure the contribution of task-frontier expansion to regional structural transformation and the college wage premium. The economy has a high-skill service sector and a second sector that combines manufacturing and low-skill services, which we call manufacturing for brevity.

4.1 Environment

Regions and Workers. The economy consists of N discrete locations indexed by subscripts n, n', corresponding to commuting zones. Each region is endowed with a measure H_n of residential floor space. There are two sectors indexed by superscripts $k \in \{M, S\}$: Manufacturing (M), and High-skill services (S). As in the simple model, there are two types of individuals $i \in \{\ell, c\}$: non-college workers (ℓ) and college graduate (c). Total mass of college graduates in a country is exogenous and given by: $\overline{L}_c = \sum_{n=1}^{N} L_{cn}$. Non-college workers are immobile across locations, while college workers may migrate across regions.[17] Labor markets are competitive.

Preferences. Individuals ψ of type $i \in \{\ell, c\}$ residing in region n have Cobb–Douglas preferences over composite consumption and residential floor space. The skill-specific expenditure share on

[17] In the US, university graduates are substantially more mobile across regions. We therefore allow college workers to respond to regional differences in wages, service prices, and housing costs.

consumption is μ_i, and that on housing is $1-\mu_i$. Utility of the individual worker is given by

$$u_{in}^{\psi} = b_n^{\psi} \left(\frac{C_{in}}{\mu_i}\right)^{\mu_i} \left(\frac{h_{in}}{1-\mu_i}\right)^{1-\mu_i}, \tag{16}$$

where b_n^{ψ} denotes idiosyncratic preference shock related to living in n, C_{in} is composite consumption, and h_{in} denotes residential floor space. An idiosyncratic shock b_n^{ψ} captures exogenous differences in location attractiveness unrelated to production.

Composite consumption is a CES aggregator of manufacturing goods and high-skill services, with elasticity of substitution $\sigma \in (0,1)$:

$$C_{in} = \left[\left(\alpha^M\right)^{\frac{\sigma-1}{\sigma}} \left(Q_{in}^M\right)^{\frac{\sigma-1}{\sigma}} + \left(\alpha^S\right)^{\frac{\sigma-1}{\sigma}} \left(Q_{in}^S\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{17}$$

where Q_{in}^M denotes aggregate manufacturing consumption, Q_{in}^S the consumption of high-skill services, and α^M, α^S the preference weights.

Prices. Manufacturing goods are freely traded across regions and differentiated by origin. Regional manufacturing consumption is a CES composite with elasticity of substitution $\beta > 1$:

$$Q_{in}^M = \left[\sum_{n'=1}^{N} \left(q_{inn'}^M\right)^{\frac{\beta-1}{\beta}}\right]^{\frac{\beta}{\beta-1}}, \tag{18}$$

where $q_{inn'}^M$ denotes consumption in region n of manufacturing goods produced in region n'. Cost minimization implies the standard manufacturing price index,

$$P^M = \left[\sum_{n'=1}^{N} \left(p_{n'}^M\right)^{1-\beta}\right]^{\frac{1}{1-\beta}}. \tag{19}$$

High-skill services are non-tradable and locally supplied. The non-tradability of services reflects the localized nature of many skill-intensive service activities. Let P_n^S denote the service price in region n. The CES price index for composite consumption is

$$\mathbb{P}_n = \left[\left(\frac{P^M}{\alpha^M}\right)^{1-\sigma} + \left(\frac{P_n^S}{\alpha^S}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{20}$$

Tasks. As in Section 3, production uses a continuum of tasks indexed by $j \in \mathfrak{R}_+$. Workers differ in comparative advantage across tasks. When performing task j, the productivity of a worker of type $i \in \{\ell, c\}$ is $z_{\ell j} = e^{-\theta_\ell j}$ and $z_{cj} = e^{-\theta_c j}$, where $\theta_\ell > \theta_c$. Therefore, college workers have a comparative advantage in higher-indexed tasks.

Producing one unit of task j in region n using labor type-i requires $\left(a_{in} z_{ij}\right)^{-1}$ units of labor, where a_{in} is task-neutral productivity of type i labor in region n. Given wages $w_{\ell n}$ and w_{cn}, the unit cost of task j is therefore

$$\gamma_{jn} = \min\left\{ \frac{w_{\ell n}}{a_{\ell n} z_{\ell j}},\ \frac{w_{cn}}{a_{cn} z_{cj}} \right\}. \tag{21}$$

Cost minimization implies that there exists a unique threshold j_n^* such that non-college workers perform all tasks $j \leq j_n^*$ and college workers perform all tasks $j > j_n^*$. This threshold is implicitly defined by

$$\frac{w_{\ell n}}{w_{cn}} = \frac{a_{\ell n}}{a_{cn}} \frac{z_{\ell j_n^*}}{z_{c j_n^*}} = \frac{a_{\ell n}}{a_{cn}} e^{-(\theta_\ell - \theta_c) j_n^*}. \tag{22}$$

Equation (22) provides a direct mapping between the local skill premium and task assignment.

Manufacturing. Manufacturing firms use a fixed continuum of tasks $j \in [0, 1]$. The production technology is a CES aggregate of tasks with elasticity of substitution $\varepsilon < 1$: $Y_n^M = A_n^M \left[\int_0^1 x_{jn}^{M\,\frac{\varepsilon-1}{\varepsilon}}\, dj\right]^{\frac{\varepsilon}{\varepsilon-1}}$, where A_n^M is manufacturing productivity and x_{jn}^M denotes the quantity of task j used in production. Cost minimization implies that the price of manufacturing goods produced in region n satisfies

$$p_n^M = \frac{1}{A_n^M}\left[\int_0^1 \gamma_{jn}^{1-\varepsilon}\, dj\right]^{\frac{1}{1-\varepsilon}} \tag{23}$$

High-Skill Services. High-skill services are produced locally using tasks on the interval $[0, J_n]$, where J_n denotes the local task frontier. Service production is given by $Y_n^S = A_n^S \left[\int_0^{J_n} x_{jn}^{S\,\frac{\varepsilon-1}{\varepsilon}}\, dj\right]^{\frac{\varepsilon}{\varepsilon-1}}$, where A_n^S is high-skill service productivity.[18] Cost minimization implies the service price

$$P_n^S = \frac{1}{A_n^S}\left[\int_0^{J_n} \gamma_{jn}^{1-\varepsilon}\, dj\right]^{\frac{1}{1-\varepsilon}} \tag{24}$$

The service price depends on three objects: service productivity A_n^S, task costs γ_{jn}, and the task frontier J_n. Expanding the task frontier affects service production through two distinct channels. First, holding task prices fixed, using a larger set of tasks raises production costs when tasks are complementary ($\varepsilon < 1$). Second, task expansion induces general-equilibrium reallocation of tasks across skill groups, lowering the marginal cost of inframarginal service tasks.[19]

[18] We treat high-skill services as nontradable because many activities in this sector, including health and education, are supplied locally. Some business and professional services are traded across regions. Conditional on market access, a location's advantage in supplying these services can be represented in reduced form by its service productivity, A_n^S.

[19] A broader task set may also raise service productivity by enabling new service capabilities, improving service quality, or facilitating more efficient production. We allow such gains to be implicitly reflected in A_n^S, but do not impose a relationship between A_n^S and J_n in the baseline model. Section 5.2 discusses how universities facilitate task creation and adoption, and Appendix B.1 provides a microfoundation for the relationship between universities and the equilibrium task frontier. In Section 6.2 we examine the sensitivity of our counterfactual results to the specification $A_n^S \propto J_n^\phi$ with positive parameter ϕ.

The key asymmetry is that manufacturing uses a fixed task set, whereas the tasks used in high-skill services vary across regions. This is the sole source of differential structural transformation in the model. We assume a common task elasticity across sectors so that regional differences arise from variation in task frontiers rather than sector-specific task technologies. In this sense, we implicitly assume very slow diffusion of technology across locations, consistent with empirical evidence, including Kalyani et al. (2025).

4.2 Universities

High-skill service production draws on a large set of tasks, but regions differ in how many of these tasks they use, summarized by a region-specific task frontier J_n, which determines the range of tasks $j \in [0, J_n]$ used in production. While not explicitly modeled, universities create new tasks potentially via its research activity and proximity to universities lowers adoption costs by local firms, due to knowledge spillovers, access to specialized talent, laboratories, and opportunities for experimentation[20] This mechanism is consistent with the evidence in Section 2.2, where regions with highly ranked universities exhibit greater exposure to occupations with newly emerging job titles. Some anecdotal examples illustrate this mechanism. In Silicon Valley, Stanford-linked advances in computing and design diffused into local financial and business services. In Pittsburgh, Carnegie Mellon's Robotics Institute catalyzed computer vision and automation tasks that later generated new allocations in industrial and health services. In both cases, universities combine research, specialized talent, and opportunities for experimentation, facilitating the local adoption of new tasks.

In Appendix C we formalize these channels. Before production, firms choose a menu of tasks and incur the associated sunk implementation cost. Universities increase the adopted frontier by expanding the set of locally available tasks and reducing the marginal cost of implementing them. We summarize this equilibrium relationship as:

$$J_n = F\left(A_n^R, U_n\right), \tag{25}$$

where A_n^R captures regional innovation fundamentals and U_n measures university presence and quality. The function $F(\cdot, \cdot)$ is increasing in both arguments. Our quantitative analysis does not estimate the underlying task-creation and adoption technologies. Instead, it recovers the equilibrium adopted frontier J_n from sector-specific employment and wage bills.

[20] Evidence on spillovers from universities to local innovation and economic activity includes Valero and Van Reenen (2019), Moretti (2021), Hausman (2022), and Bergeaud et al. (2025).

Universities may also be associated with changes in the productivity of college relative to non-college workers, $a_{cn}/a_{\ell n}$. In the quantitative analysis, we distinguish this margin from task-frontier expansion because the former changes the cost of assigning existing tasks across skill groups, whereas the latter expands the set of tasks used in high-skill service production. We estimate this relative productivity and examine its variation across regions and over time.

4.3 Market Clearing

Labor Mobility. College workers are mobile across regions, while non-college workers are immobile. Given preferences (16), the value of locating in a particular region, n, for an individual college worker with a specific idiosyncratic preference vector, $\mathbf{b} = \{b_n\}_{n=1}^{N}$, is:

$$v_{cn}(\mathbf{b}) = b_n \frac{w_{cn}}{\mathbb{P}_n^{\mu_c} r_n^{1-\mu_c}} \tag{26}$$

In equilibrium, college workers move to the location where they receive the highest utility so that $v_c(\mathbf{b}) = \max_{n \in \mathcal{R}} v_{cn}(\mathbf{b})$. We assume that idiosyncratic preferences are drawn independently across individuals and locations from a Fréchet distribution: $G_n(b) = e^{-B_n b^{-\kappa}}$, where $\kappa > 1$. The scale parameter B_n captures the average value of amenities in region n, and the shape parameter κ controls the dispersion of idiosyncratic preferences, and hence the responsiveness of location decisions to economic variables relative to idiosyncratic preferences. Using the Fréchet distribution, we can show that the fraction of college workers in each city is:

$$\frac{L_{cn}}{\overline{L}_c} = \frac{B_n w_{cn}^{\kappa} \left(\mathbb{P}_n^{\mu_c} r_n^{1-\mu_c}\right)^{-\kappa}}{\sum_{n'=1}^{N} B_{n'} w_{cn'}^{\kappa} \left(\mathbb{P}_{n'}^{\mu_c} r_{n'}^{1-\mu_c}\right)^{-\kappa}}. \tag{27}$$

Goods Market Clearing. Manufacturing goods are tradable and differentiated by region of production. Let X_n^M denote total expenditure on manufacturing goods produced in region n. Goods market clearing implies:

$$X_n^M = \left(p_n^M\right)^{1-\beta} \left(P^M\right)^{-(1-\beta)} \sum_{n'=1}^{N} \sum_{i=\ell,c} \mu_i \frac{w_{in'} L_{in'}}{\mathbb{P}_{n'}^{1-\sigma}} \left(\frac{P^M}{\alpha^M}\right)^{1-\sigma}. \tag{28}$$

High-skill services are non-tradable. Let X_n^S denote total expenditure on services produced in region n. Market clearing requires

$$X_n^S = \sum_{i=\ell,c} \mu_i \frac{w_{in} L_{in}}{\mathbb{P}_n^{1-\sigma}} \left(\frac{P_n^S}{\alpha^S}\right)^{1-\sigma} \tag{29}$$

Labor Market Clearing. In each region, firms hire labor to produce tasks used in manufacturing and high-skill services. Because markets are competitive and production exhibits constant returns to scale, labor market clearing condition for non-college workers in each region requires that the total payment for non-college workers ($w_{\ell n}L_{\ell n}$) equals the sum of payments to workers in the production of tasks used in manufacturing and high-skill services:

$$w_{\ell n}L_{\ell n} = \left(1-\lambda_{cn}^{M}\right)X_n^M + \lambda_{\ell n}^{S}X_n^S, \tag{30}$$

$$w_{cn}L_{cn} = \lambda_{cn}^{M}X_n^M + \left(1-\lambda_{\ell n}^{S}\right)X_n^S, \tag{31}$$

where λ_{in}^k denotes the share of sector-k revenue accruing to labor type i in region n:

$$\lambda_{cn}^M = \int_{j_i^*}^{1} \frac{\gamma_{jn}^{1-\varepsilon}}{\int_0^1 \gamma_{j'n}^{1-\varepsilon}dj'}dj, \quad \lambda_{\ell n}^S = \int_0^{j_n^*} \frac{\gamma_{jn}^{1-\varepsilon}}{\int_0^{J_n} \gamma_{j'n}^{1-\varepsilon}dj'}dj \tag{32}$$

These shares are determined endogenously by task assignment and depend on the task threshold j_n^* and the sectoral task sets.

Housing Market Clearing. Residential floor space in region n is fixed at H_n. Residential floor space market clearing implies that rents adjust to equate supply and demand:

$$r_n = \frac{1}{H_n}\sum_{i=\ell,c}(1-\mu_i)w_{in}L_{in}. \tag{33}$$

An inflow of college workers raises housing demand and rents, generating a dispersion force that guarantees the unique equilibrium. We assume absentee ownership for housing.

4.4 General Equilibrium

The economy is characterized by regional differences in productivity, amenities, housing supply, innovation fundamentals, and university presence. The task frontier J_n is taken as given by firms and determined in reduced form by (25). We now define the equilibrium.

Definition 1 (General Equilibrium). *Given the model primitives and economy-wide parameters, an equilibrium consists of wages $\{w_{in}\}$, the spatial distribution of college workers $\{L_{cn}\}$, task thresholds $\{j_n^*\}$, and rents $\{r_n\}$ such that:*

(i) Tasks are allocated across skill groups to minimize unit costs, satisfying (21) and defining the task threshold j_n^*;

(ii) Firms maximize profits subject to their technologies, prices satisfy zero-profit conditions (23) and (24);

(iii) *Goods, labor, and housing markets clear in each region, satisfying conditions* (28)–(33)*;*

(iv) *College workers choose locations optimally and satisfy* (27)*;*

(v) *The distribution of college graduates satisfies* $\sum_n L_{cn} = \bar{L}_c$*, and all quantities are non-negative.*

We summarize here the main mechanisms through which universities affect regional outcomes. Consider a region with a strong university presence, reflected in a high value of U_n. For a given innovation shock, A_n^R, universities help expand the local task frontier J_n. Because frontier tasks are skill intensive, task expansion raises the relative demand for college labor and increases the college wage premium, as shown in Proposition 2. Universities may also raise the relative productivity of college workers, $a_{cn}/a_{\ell n}$, which further amplifies wage differences.

Expansion of the task frontier also changes task assignment. As the college wage rises, some inframarginal tasks are reassigned from college to non-college workers, shifting the task threshold j_n^*. This reallocation affects service production costs. At the same time, newly adopted frontier tasks are performed by college workers whose wages have increased. As a result, the effect on local service prices is ambiguous. College workers respond to changes in real income. Higher wages increase the attractiveness of regions with stronger universities, while changes in high-skill service prices and housing costs can either reinforce or offset this force. Therefore, migration, task assignment, wages, prices, and housing rents are jointly determined in equilibrium. In subsequent sections, we quantify the importance of these mechanisms using U.S. commuting-zone data.

5 Model Estimation

5.1 Parametrization

Most technology and preference parameters are standard and taken from the literature. Table D.1 in the Appendix reports their values and sources. We set the elasticity of substitution between tasks to $\varepsilon = 0.5$ following Humlum (2019). The elasticity of substitution between manufacturing and high-skill services in consumption is set to $\sigma = 0.5$, and the trade elasticity to $\beta = 4$. Following Diamond (2016), we set the housing expenditure share $1 - \mu_c$ and $1 - \mu_\ell$ to 0.4. The migration parameter is set to $\kappa = 2$, consistent with the the average elasticity of employment with respect to real wages estimated in Fajgelbaum et al. (2019). The key parameters for the quantitative analysis govern comparative advantage across tasks. As discussed in Section 4.1, we parametrize task productivity as: $z_{\ell jt} = e^{-\theta_\ell j}$ and $z_{cjt} = e^{-\theta_c j}$. The parameters (θ_ℓ, θ_c) determine how comparative advantage varies with task complexity. Estimating these parameters directly from wage data is challenging because task assignment, wages, and employment are jointly determined in equilibrium. We therefore discipline (θ_ℓ, θ_c) outside the wage equations. Since equilibrium task assignment depends only on relative slopes and levels, we normalize $\theta_\ell = 1$ and set $\theta_c = 0.5$ in the baseline. We also show our counterfactual results are not sensitive to the choice of θ in Section 6.2.

5.2 Model Inversion

We next use the observed data and the structure of our model to recover unobserved variables, such as sectoral-level productivity, prices, amenities and task frontiers, which are inputs into our counterfactual exercise. The next proposition summarizes the inversion of these unobserved variables.

Proposition 4 (Inversion of Regional Fundamentals). *Given the elasticity of substitution in production (ε), technology parameters (θ_c, θ_ℓ), demand parameters ($\mu_c, \mu_\ell, \alpha^M, \alpha^S, \sigma, \beta$) and data by region n and period t on employment by sector and type ($L^M_{cnt}, L^M_{\ell nt}, L^S_{cnt}, L^S_{\ell nt}$), wages by type ($w_{nct}, w_{\ell nt}$), and floor space rent (r_{nt}), there exist unique values of adjusted productivity by sector ($\widetilde{A}^M_{nt}, \widetilde{A}^S_{nt}$), regional amenities ($B_{nt}$), floor space endowment (H_{nt}), task thresholds (j^*_{nt}), task frontier (J_{nt}), and relative productivity of college workers ($\zeta_{nt} = a_{cnt}/a_{\ell nt}$) that are consistent with the data being an equilibrium of the model.*

While the formal derivations are presented in Appendices D.2 and D.3, we outline here the intuition behind the model inversion. First, the task threshold (j^*_{nt}) and task frontier (J_{nt}) are recovered from relative wage bills across sectors. The key source of identification is that manufacturing and high-skill services differ in the range of tasks they employ. Manufacturing uses a fixed unit mass of tasks. As a result, the ratio of wage bills of college to non-college workers in manufacturing, $(w_{cnt}L^M_{cnt})/(w_{\ell nt}L^M_{\ell nt})$, is pinned down by the task threshold j^*_{nt} for given parameters. High-skill services employ tasks over the endogenous interval $[0, J_{nt}]$. Therefore, the corresponding wage-bill ratio in services, $(w_{cnt}L^S_{cnt})/(w_{\ell nt}L^S_{\ell nt})$, depends both on the task threshold j^*_{nt} and the frontier of tasks J_{nt}. Taken together, these two equilibrium relationships jointly identify the task threshold and the task frontier for each region and period.[21]

[21] The inversion requires an interior task threshold and wage bill ratios consistent with $J_{nt} > 1$. Appendix Proposition D.1 states the sufficient conditions and provides the proof.

Second, conditional on task assignment and observed wages, we recover sectoral prices and productivity using goods market clearing and zero-profit conditions. For manufacturing, unit costs are CES aggregates of task-level labor costs, which depend on observed wages and the inferred task threshold. Then, adjusted manufacturing prices ($\widetilde{p}_{nt}^{M} = p_{nt}^{M}/\alpha^{M}$) are proportional to this unit cost index divided by adjusted productivity ($\widetilde{A}_{nt}^{M}$). Together with the CES demand structure, they identify adjusted productivity up to a normalization. High-skill services are non-traded, so local market clearing determines prices (P_{nt}^{S}) and adjusted productivity ($\widetilde{A}_{nt}^{S}$) in each region. Combining manufacturing and service prices yields a region-specific consumption price index ($\mathbb{P}_{nt}$).

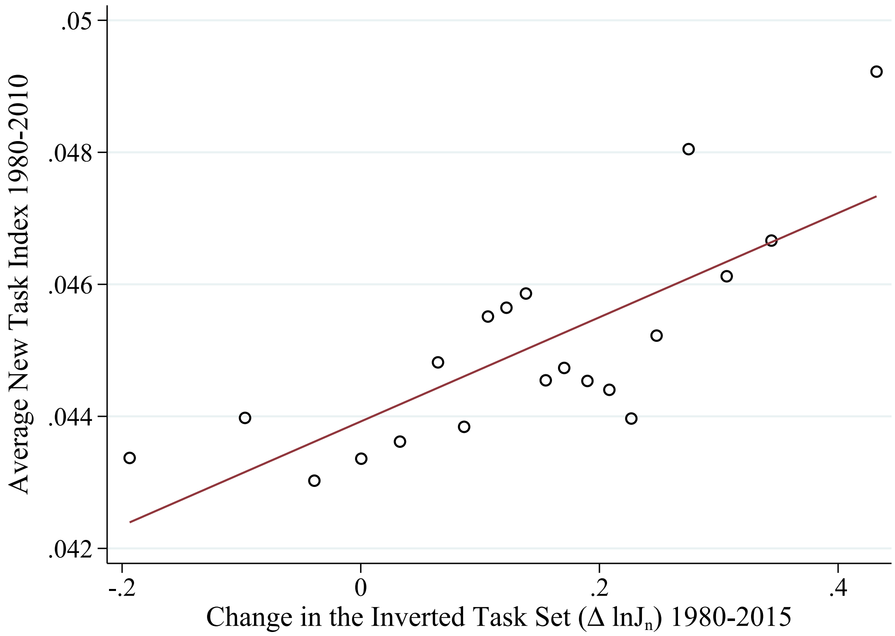
Lastly, we recover other location fundamentals, amenities (b_{nt}) and floor space endowment (H_{nt}), using spatial equilibrium conditions. With the optimal location choice of college graduates, observed wages, local prices, and rents allow us to back out the value of amenities as the residual that rationalizes the observed sorting. Intuitively, regions that attract college workers despite lower wages or higher prices must offer higher amenities. Floor space endowments are recovered from the housing market clearing. In a nutshell, these two steps deliver region-specific amenities and housing supply shifters that exactly rationalize the observed spatial distribution of workers and prices as an equilibrium. As with prices and productivity, these objects are identified up to a normalization, which is sufficient for subsequent counterfactual analysis.

5.3 External Validation of the Recovered Task Frontier

The task frontier, (J_n), is recovered from sector-specific employment and wage bills by skill group. We assess the external validity of this model-implied object by comparing it with the New Task Index introduced in equation (2). Both measures capture aspects of new task creation, they represent distinct concepts. In the model, J_n denotes the task frontier and the set of tasks used in high-skill service production, so an increase in J_n reflects an expansion of the task set through the introduction of new tasks. By contrast, the New Task Index proxies for the local employment share of newly emerging tasks. Because the task frontier has no direct empirical counterpart, the New Task Index provides a natural, albeit indirect, benchmark for validation.

Despite capturing different dimensions of task creation and adoption, both measures indicate the extent to which new tasks are present in a local economy. Moreover, because they are constructed from independent different data sources, any relationship between them is not mechanical. Figure 6 shows that commuting zones with larger increases in the recovered task frontier

Figure 6: Recovered Task-Frontier Growth and the New Task Index



Notes: This figure presents a binscatter plot relating the change in the recovered task frontier between 1980 and 2015 to the average New Task Index across 1990, 2000, and 2010. The New Task Index is defined in equation (2). The commuting zones are divided into 20 equal-sized bins based on $\Delta \ln J_n$, and each circle reports the mean of both variables within a bin. The fitted line is estimated using the underlying commuting-zone-level observations.

also exhibit greater employment exposure to newly emerging tasks. The strong positive association indicates that the model-implied task frontier reproduces meaningful geographic variation in the prevalence of new work observed in the data. As shown in Appendix D.4, this relationship remains robust after controlling for initial local labor market characteristics.

5.4 *Universities, Task Expansion and Productivity Growth*

We now turn to the role of universities in shaping local task adoption and relative productivity difference between skills, both of which, in turn, contribute to regional difference in skill premium. In our theory, universities affect local labor markets by expanding the set of tasks that are adopted in high-skill services. This expansion of the task frontier, $\Delta \ln J_{nt}$, reshapes equilibrium task assignment and increases demand for skilled labor. Changes in relative productivity of college workers, $\Delta \ln \zeta_n = \Delta \ln(a_{cnt}/a_{\ell nt})$, i.e., skill-biased technical change, enter our quantitative analysis as a traditional mechanism for skill premium.

We relate changes in both location-specific variables to the presence of a university together with its quality, as in our empirical exercise in Section 2.2, using long differences between 1980 and 2015. The identifying assumption is that, conditional on baseline covariates, unobserved changes in task demand by high-skill services and relative productivity are orthogonal to university rankings. To mitigate concerns that universities are systematically located in regions with stronger growth potential, the regressions include control variables that capture pre-existing regional scale and composition of the labor market. Details of the specification are relegated to Appendix D.5.

Table 2: Universities, Task Expansion, and Productivity Changes

	$\Delta \ln J_n$		$\Delta \ln \zeta_n$	
	(1)	(2)	(3)	(4)
University Rank=1	0.148***	0.158***	0.159***	0.081***
	(0.017)	(0.024)	(0.019)	(0.026)
University Rank=2	0.071***	0.080***	0.084***	0.029
	(0.022)	(0.025)	(0.026)	(0.030)
University Rank=3	0.077***	0.071***	0.066***	0.028
	(0.020)	(0.022)	(0.025)	(0.027)
University Rank=4	0.022	0.008	0.040*	0.012
	(0.017)	(0.019)	(0.024)	(0.025)
Log Employment in 1980		0.034		-0.037
		(0.027)		(0.035)
Log High-Skill Service Employment in 1980		0.134***		-0.016
		(0.037)		(0.050)
Log College Workers in 1980		-0.161***		0.074**
		(0.030)		(0.037)
Observations	674	674	674	674
R-squared	0.100	0.151	0.063	0.088

Notes: In Columns (1)-(2), we regress changes in task frontier between 1980 and 2015, $\ln J_{nt}$, on indicators for university quality, measured by the rank of the best university in each region, together with predetermined regional controls. University-rank indicators are defined relative to regions with no ranked university or with a university ranked below 400, which form the omitted category. The regression includes three controls: the logarithm of total employment in 1980; the logarithm of high-skill service employment in 1980; and the logarithm of college-educated employment in 1980. Columns (3)-(4) regress changes in relative productivity of college workers, $\Delta \ln \zeta_n = \Delta \ln \left(a_{cnt}/a_{\ell nt}\right)$, on the same university-rank indicators and baseline controls. Robust standard errors are reported in parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

Columns (1)–(2) of Table 2 report the results on task frontier. The estimates show a strong and monotonic relationship between the presence of a good university and task expansion. Regions hosting top-300 universities experience statistically significant increases in the task frontier relative to regions with a low-ranked university or none. The largest task expansions are observed for regions hosting top-ranked universities, where the task frontier expands by around 15 percent relative to the control group. This finding aligns with the empirical Fact 3 and provides further support for the task channel assumed in the model.

Columns (3)–(4) examine the variation of changes in relative task-neutral productivity across regions. The estimated coefficients suggest that regions hosting top-ranked universities tend to experience stronger increases in the relative productivity of skilled labor, or stronger skill-biased technical change. While not modeled explicitly, this productivity difference reinforces the impact of task expansion on skill premium, despite with different implications for the task allocation and structural change.

6 Counterfactual Analysis

We now use the estimated model to quantify the contribution of task-frontier expansion in university regions to structural transformation and wage inequality. Section 5.4 shows that growth in the high-skill service task frontier is concentrated in commuting zones hosting top-ranked universities. As documented in Section 2.2, these regions also experienced the largest increases in high-skill-service employment and the college wage premium. Our counterfactual analysis therefore asks how much of these changes can be attributed to the expansion of the task frontier.

Our baseline counterfactual removes task-frontier growth in commuting zones hosting a top-100 university. Specifically, we set the task frontiers in 2015 equal to their 1980 values, $J^{\mathrm{CF}}_{n,2015} = J_{n,1980}$, and leave the task frontier unchanged elsewhere.[22] We also consider an experiment that removes both the task-frontier growth and changes in the relative productivity of college workers, that is, $J^{\mathrm{CF}}_{n,2015} = J_{n,1980}$ and $\zeta^{\mathrm{CF}}_{n,2015} = \zeta_{n,1980}$ for top-university commuting zones. In all counterfactuals, other estimated regional fundamentals, including amenities, housing supply, and sectoral productivities remain fixed at their 2015 values. Non-college employment remains fixed within each commuting zone. College workers are held constant in the aggregate, but they may reallocate across locations. We then solve for counterfactual wages, task assignment, sectoral prices and expenditures, and the spatial distribution of college workers. The outcomes of interest are the high-skill service share of employment and value added, as well as the college wage premium. Together, these outcomes capture the contribution of task-frontier expansion to both structural transformation and inequality.

[22] Appendix Figure E.1 displays the baseline and counterfactual task frontier in 2015 across commuting zones.

6.1 *Main Counterfactual Results*

Our central finding is that task-frontier expansion in top-university regions accounts for a substantial share of the growth of high-skill services between 1980 and 2015. Eliminating this expansion reduces both the value-added and employment shares of high-skill services and lowers the college wage premium in regions that host top-ranked universities.

Table 3 reports the observed changes in high-skill service value-added and employment shares between 1980 and 2015, followed by two counterfactuals. The second row removes task-frontier growth in top-university regions, while the third also removes changes in the relative productivity of college workers. Holding the task frontier fixed reduces the increase in the high-skill service value-added share in top-university commuting zones from 17.1 to 11.7 percentage points. Task-frontier expansion therefore accounts for 5.4 percentage points, or approximately 32 percent, of the observed increase. The employment effect is smaller but economically meaningful. Removing task-frontier expansion reduces growth in the high-skill service employment share from 13.9 to 11.2 percentage points. The task-frontier channel thus accounts for 2.7 percentage points, or 19 percent, of the observed increase. The larger effect on value added indicates that task expansion alters sectoral labor intensity as well as the allocation of workers across sectors.[23]

Additionally holding fixed the relative productivity of college workers lowers growth in the high-skill service value-added share only slightly further, from 11.7 to 11.3 percentage points. Thus, most of the structural transformation generated by the model operates through task-frontier expansion rather than changes in the relative productivity of college labor. The employment effects are less monotonic because relative productivity simultaneously influences wages, task assignment, and migration, generating offsetting general-equilibrium adjustments. Taken together, the results identify task-frontier expansion as the primary mechanism through which the model accounts for the growth of high-skill services in top-university regions.

Although the counterfactual directly changes J_n only in top-university commuting zones, it also reduces high-skill service growth elsewhere. Value-added-share growth falls by 1.7 percentage points in commuting zones with other universities and by 1.6 percentage points in those without a university. The corresponding reductions in employment-share growth are 2.2 and 2.0 percentage points. These spillovers arise because the contraction of skill-intensive activity in

[23]Task-frontier expansion affects both the scale of the high-skill service sector and the quantity and composition of labor required for production. Sectoral employment therefore need not change one-for-one with sectoral value added.

Table 3: Task-Frontier Expansion in Top-University Regions and Structural Transformation

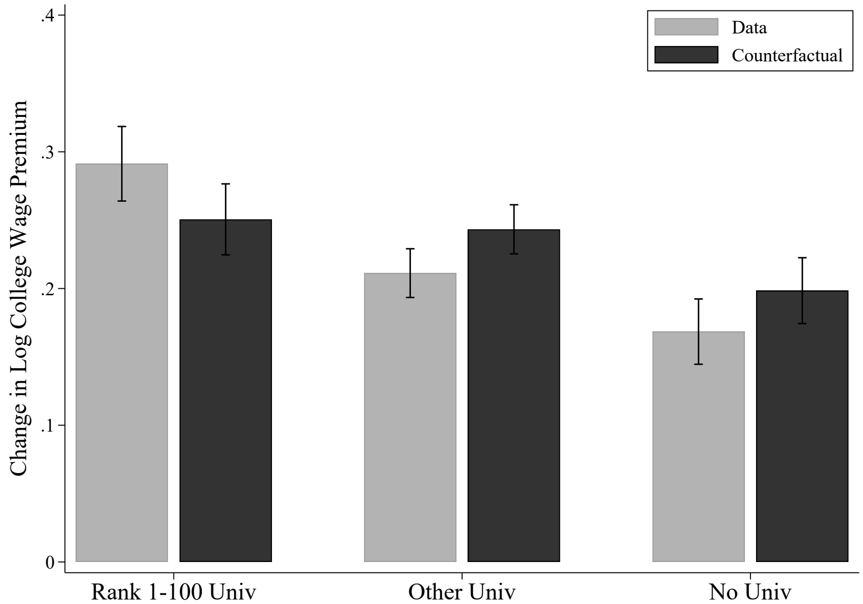
	Change in High-Skill Service					
	Value-Added Share			Employment Share		
	Top 100	Other Univ.	No Univ.	Top 100	Other Univ.	No Univ.
Observed change in 1980–2015	17.11 (0.63)	12.85 (0.34)	10.52 (0.40)	13.91 (0.58)	10.66 (0.31)	8.67 (0.37)
Shut down changes in task frontier J_n	11.71 (0.57)	11.13 (0.33)	8.91 (0.39)	11.22 (0.59)	8.50 (0.30)	6.69 (0.36)
Shut down changes in task frontier J_n and relative productivity of college workers ζ_n	11.29 (0.56)	10.15 (0.33)	7.95 (0.39)	11.75 (0.57)	8.13 (0.30)	6.26 (0.36)
Contribution of J_n, Top 100	31.6 percent			19.3 percent		
Contribution of J_n and ζ_n, Top 100	34.0 percent			15.6 percent		

Notes: The first three rows report mean changes from 1980 to observed or counterfactual 2015, in percentage points. Standard errors across commuting zones are reported in parentheses. The contribution of each counterfactual channel is based on the difference between the observed and counterfactual changes, and the percentage explained divides this contribution by the observed change in top-university commuting zones. "Other Univ." denotes commuting zones with a university but no top-100 institution.

top-university regions changes the demand for college labor and its spatial allocation. Because high-skill services are locally produced and consumed, these adjustments affect local income, service demand, and task assignment throughout the economy. Untreated regions therefore do not fully absorb the activity displaced from top-university regions; instead, high-skill service growth slows across all region types.

Task-frontier expansion affects not only the size of the high-skill service sector but also the spatial distribution of skill demand. Figure 7 compares changes in the college wage premium between 1980 and 2015 in the data and the counterfactual. Removing task-frontier expansion lowers the college wage premium in top-university commuting zones by 4.1 percent relative to the observed change. By contrast, the premium increases by 3.2 percent in commuting zones with other universities and by 3.0 percent in those without a university. This pattern reflects general equilibrium adjustment across regions. A contraction in the task frontier eliminates tasks in which college workers have a comparative advantage, reducing the relative demand for college labor in top-university regions. The resulting decline in local skill premia induces college workers to relocate, thereby affecting service demand, wages, and task assignment elsewhere. These spatial adjustments raise skill-premium growth in regions whose task frontiers are unchanged. Consequently, the counterfactual economy exhibits substantially less regional dispersion in college

Figure 7: Task-Frontier Expansion in Top-University Regions and the College Wage Premium



Notes: The figure reports mean changes in the logarithm of the college wage premium between 1980 and observed or counterfactual 2015. The counterfactual sets the 2015 task frontier (J_n) equal to its 1980 level in commuting zones hosting top-100 universities. Vertical lines report 95 percent confidence intervals based on variation across commuting zones. The sample contains 66 commuting zones with a top-100 university, 345 commuting zones with another university, and 263 commuting zones without a university.

wage premia. Task-frontier expansion therefore contributes not only to the rise in the college wage premium in top-university regions but also to the widening of geographic disparities in the returns to skill.

6.2 *Robustness and Sensitivity*

The main counterfactual results are robust to alternative assumptions about migration, comparative advantage, and the productivity effects of task-frontier expansion. Appendix Tables E.1–E.4 report these results.

Fixed Spatial Distribution of College Workers. In the baseline counterfactual, college workers relocate in response to changes in wages, prices, and housing costs. We repeat the exercise while holding college employment fixed at its observed 2015 level in each commuting zone. Panel A of Appendix Tables E.1 and E.2 shows that task-frontier expansion accounts for 5.71 percentage points of the increase in the high-skill service value-added share, 3.06 percentage points of the increase in its employment share, and approximately 3.3 percent of the increase in the college wage premium in top-university regions. Thus, most of the effect operates within regions through task reassignment and shifts in relative labor demand, while migration plays a secondary offsetting role.

Alternative Comparative Advantage Parameters. We repeat the estimation and counterfactual analysis using $\theta_c = 0.25$ and $\theta_c = 0.75$, relative to the baseline value $\theta_c = 0.50$, recalibrating regional fundamentals in each case. Panels B.1 and B.2 of Appendix Tables E.1 and E.2 show that the contribution of task-frontier expansion to high-skill service growth is largely unchanged. The wage premium effect is more sensitive, ranging from 6.1 percent when $\theta_c = 0.25$ to 2.2 percent when $\theta_c = 0.75$. Alternative values of θ_c therefore affect whether adjustment occurs primarily through wages or task reassignment, but not the overall contribution of task-frontier expansion to structural transformation.

Productivity Gains from Task Expansion. The baseline counterfactual holds service productivity fixed, thereby isolating the task-composition channel. We alternatively allow productivity to depend on the task frontier according to $A_n^S \propto J_n^{\phi}$. Appendix Tables E.3 and E.4 show that task-frontier expansion accounts for 4.24 percentage points of the increase in the high-skill service value-added share when $\phi = 0.5$ and 3.11 percentage points when $\phi = 1$, compared with 5.41 percentage points in the baseline. The corresponding employment-share effects are 1.56 and 0.48 percentage points. Intuitively, allowing task expansion to raise productivity introduces an offsetting general-equilibrium effect: in the counterfactual, a lower task frontier also reduces service productivity and raises service prices, partially sustaining nominal expenditure and labor demand. The estimated effects are therefore smaller, but the qualitative conclusion remains unchanged: task-frontier expansion is an important driver of high-skill service growth and the rising college wage premium.

7 Conclusion

Why did some regions transition from manufacturing to high-skill services more rapidly than others? This paper highlights the role of universities in expanding the range of tasks used in local production. We document that regions with universities, especially highly ranked research institutions, experienced larger increases in high-skill service employment shares and the college wage premia, as well as a greater concentration of employment in occupations associated with newly emerging tasks.

To interpret these findings, we develop a task-based theory of local structural transformation. Workers differ in their comparative advantage across tasks, and high-skill services draw on a broader range of tasks than manufacturing. Universities affect local economies through college labor supply, relative college workers' productivity, and the creation and adoption of new tasks. An increase in college labor supply lowers the college wage premium and reallocates existing tasks toward college workers. An expansion of the task frontier instead introduces skill-intensive tasks, raises the relative demand for college labor, and induces the reassignment of some existing tasks toward non-college workers. As a result, the new-task channel can jointly account for the growth of high-skill services and the rise in the college wage premium.

We embed this mechanism in a quantitative spatial model with worker mobility. The sector-by-skill wage bills identify regional task frontiers and distinguish changes in task frontiers from changes in the relative productivity of college workers. We then consider a counterfactual that removes task-frontier growth in commuting zones with a top-100 university, holding other regional fundamentals fixed. Task-frontier growth accounts for approximately 32 percent of the observed increase in the high-skill service value-added share and 19 percent of the increase in its employment share in these regions. Without the task expansion, the college wage premium would have risen about four percentage points less. Although the counterfactual changes task frontiers only in top-university regions, its effects propagate to other regions through wages, migration, and local service demand.

The broader lesson is that structural transformation depends not only on sectoral productivity and skill supply, but also on how new tasks are used in production. When task creation is geographically concentrated, technological change reshapes both the sectoral composition of employment and the spatial distribution of skill demand. Universities matter in this process not simply as suppliers of high-skilled labor, but also as institutions associated with the creation and local adoption of new work. Identifying how university research generates new applications and specialized expertise, and how local firms adopt them through access to researchers, graduates, laboratories, and opportunities for experimentation, is an important direction for future research, particularly as emerging technologies such as artificial intelligence create new forms of work.

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Appendix to
"Universities, New Tasks, and the Rise of Services"

Chang Liu Kohei Takeda

A Proofs of Section 3

This appendix provides proofs for the results in Section 3. We let $\widetilde{L} = L_c/L_\ell$ denote the relative supply of college workers and $Z_j = z_{\ell j}/z_{cj}$ denote the relative productivity. By the single crossing assumption, $dZ_j/dj < 0$. For a candidate task threshold j, define the labor requirements for tasks performed by non-college and college workers in services as:

$$R_\ell(j) = \int_0^j \frac{1}{\varphi_k z_{\ell k}} dk, \quad R_c(j; J) = \int_j^J \frac{1}{\varphi_k z_{ck}} dk. \tag{A.1}$$

Conditional on j, service unit cost becomes $w_\ell R_\ell(j) + w_c R_c(j; J)$. Therefore, the college share of service costs is:

$$\lambda(j, \omega, J) = \frac{R_c(j; J)}{\omega R_\ell(j) + R_c(j; J)} \tag{A.2}$$

where $\omega = w_\ell/w_c$.

We also define the shares of expenditure paid to non-college and college workers:

$$\begin{aligned} S_\ell(j, \omega; J) &= \alpha\left[1 - \lambda(j, \omega, J)\right] + (1-\alpha)j, \\ S_c(j, \omega; J) &= \alpha\lambda(j, \omega, J) + (1-\alpha)(1-j) \end{aligned} \tag{A.3}$$

Using them the labor market clearing requires:

$$\omega = \frac{S_\ell(j, \omega; J)}{S_c(j, \omega; J)} \widetilde{L} \tag{A.4}$$

Substituting (A.2) into the right-hand side of (A.4) yields:

$$a_0(j)\omega^2 + a_1(j, J, \widetilde{L})\omega + a_2(j, J, \widetilde{L}) = 0 \tag{A.5}$$

where $a_0(j) = (1-\alpha)(1-j)R_\ell(j) > 0$, $a_1(j, J, \widetilde{L}) = R_c(j, J)[\alpha + (1-\alpha)(1-j)] - R_\ell(j)[\alpha + (1-\alpha)j]\widetilde{L}$, and $a_2(j, J, \widetilde{L}) = -(1-\alpha)j\widetilde{L}R_c(j; J) < 0$. Since $a_2/a_0 < 0$, the two solutions have opposite sign and equation (A.5) has a unique positive solution for any $j \in (0, 1)$, $\widetilde{L} > 0$ and finite $J > 1$. We let $\omega = \Gamma(j, J, \widetilde{L})$ refer to such a solution. Then the function Γ shows three properties.

First, an increase in j assigns additional incumbent tasks to non-college workers. Since the task costs of the two types of workers are the same at the threshold, this reassignment does not change the unit cost of service. Yet, it transfers expenditure from college to non-college labor and the relative non-college wage must rise to clear the labor market, so, $\partial\Gamma/\partial j > 0$.

Second, consider an increase in relative supply of college workers, $\widetilde{L}$. For any task assignment, a high value of $\widetilde{L}$ leads to higher relative non-college wage to clear the labor market, so $\partial\Gamma/\partial\widetilde{L} > 0$.

Third, an increase in J introduces additional tasks performed by college workers at the frontier. This raises the college wage-bill share for a given ω and j, lowering the relative non-college wage required to clear the labor market. Therefore, we have $\partial\Gamma/\partial J < 0$.

A.1 Proof of Proposition 1

An equilibrium is an intersection of $\omega = \Gamma(j, J, \widetilde{L})$ and $\omega = Z_j$. $\Gamma(j, J, \widetilde{L})$ is continuous and strictly increasing in j, and Z_j is continous and strictly decreasing. In addition $\Gamma(0; J, \widetilde{L}) = 0 < Z_0$ and $\Gamma(1; J, \widetilde{L}) > Z_1 = 0$. Therefore, the intermediate value theorem guarantees a unique interior intersection. The equilibrium task threshold j^* and relative wage ω are pinned down by the intersection.

A.2 Proof of Proposition 2

(i) From the second property above, we have $\Gamma(j; J, \widetilde{L}_1) > \Gamma(j; J, \widetilde{L}_0)$ for $\widetilde{L}_1 > \widetilde{L}_0$, for every possible threshold j. The labor market clearing schedule shifts upward while the relative productivity schedule remains unchanged. Given Z_j is strictly decreasing, the new equilibrium satisfies $j_1^* < j_0^*$ and $\omega_1 = z_{j_1^*} > z_{j_0^*} = \omega_0$.

(ii) Suppose $J_1 > J_0$. The third property above implies $\Gamma(j; J_1, \widetilde{L}) < \Gamma(j; J_0, \widetilde{L})$ for every incumbent task threshold j. The labor market clearing schedule shifts downward while the relative productivity schedule remains unchanged. Clearly, the new equilibrium satisfies $j_1^* > j_0^*$ and $\omega_1 = z_{j_1^*} < z_{j_0^*} = \omega_0$. Expansion of task frontier raises college wage premium and reallocates some incumbent tasks toward non-college workers.

A.3 Proof of Proposition 3

At the task threshold, cost minimization implies $w_\ell/z_{\ell j} = w_c/z_{cj}$, therefore,

$$\frac{1}{\varphi_{j^*} z_{\ell j^*}} = \omega^{-1} \frac{1}{\varphi_{j^*} z_{c j^*}}. \tag{A.6}$$

Define $e_{cJ} \equiv \frac{1}{\varphi_J z_{cJ}}$, $e_{cj^*} \equiv \frac{1}{\varphi_{j^*} z_{cj^*}}$, $\mathbb{A}^S = q^S/L^S$, and $\eta_Q \equiv \frac{d \log q^S}{dJ}$. Substituting (A.6) into equation (13) and dividing by L^S gives the results.

B Connections to Skill-Biased Technical Change and Structural Transformation

We first start with the general representation of the college wage premium for the two-sector economy. We define the value added share of service sector (v^S) and manufacturing sector (v^M):

$$v^S = \frac{p^S q^S}{X}, \qquad v^M = 1 - v^S \tag{B.1}$$

In addition, we let

$$\lambda_c^k = \frac{w_c L_c^k}{p^k q^k}, \qquad \lambda_\ell^k = 1 - \lambda_c^k \tag{B.2}$$

refer to the share of payment to college workers and non-college workers in sector k.

Using them, labor market clearing condition is expressed by:

$$w_c L_c = \lambda_c^S v^S X + \lambda_c^M v^M X \tag{B.3}$$

for college workers and

$$w_\ell L_\ell = \left(1 - \lambda_c^S\right) v^S X + \left(1 - \lambda_c^M\right) v^M X \tag{B.4}$$

for non-college workers. Then, we define the aggregate income share of college workers:

$$\pi_c = \lambda_c^S v^S + \lambda_c^M v^M \tag{B.5}$$

Combining (B.3) and (B.4) yields the college wage premium:

$$\frac{w_c}{w_\ell} = \frac{\pi_c}{1 - \pi_c} \frac{L_\ell}{L_c} \tag{B.6}$$

Taking its log changes gives:

$$d \ln \left(\frac{w_c}{w_\ell}\right) = -d \ln \left(\frac{L_c}{L_\ell}\right) + d \ln \left(\frac{\pi_c}{1 - \pi_c}\right), \tag{B.7}$$

where

$$d \ln \left(\frac{\pi_c}{1 - \pi_c}\right) = \frac{1}{\pi_c(1 - \pi_c)} \left((\lambda_c^S - \lambda_c^M) dv^S + v^S d\lambda_c^S + v^M d\lambda_c^M\right) \tag{B.8}$$

We therefore obtain the college wage premium decomposition as follows:

$$d \ln \left(\frac{w_c}{w_\ell}\right) = -\, d \ln \left(\frac{L_c}{L_\ell}\right) + \frac{\lambda_c^S - \lambda_c^M}{\pi_c(1 - \pi_c)}\, dv^S + \frac{v^S\, d\lambda_c^S + v^M\, d\lambda_c^M}{\pi_c(1 - \pi_c)} \tag{B.9}$$

Equation (B.9) summarizes three components that jointly determine the change in college wage premium: (i) relative supply of college to non-college workers; (ii) structural transformation between sectors; and (iii) changes in within-sector task assignment and task content.

Next, we consider service value-added and employment shares. In the simple model, Cobb-Douglas preference implies: $p^S q^S = \alpha X$ and $p^M q^M = (1-\alpha)X$, so that $v^S = \alpha$ and $dv^S = 0$. Let the labor requirement per dollar of sector k output be:

$$e^k = \frac{\lambda_c^k}{w_c} + \frac{\lambda_\ell^k}{w_\ell} \tag{B.10}$$

Using this, sectoral employment is $L^S = e^S \alpha X$ and $L^M = e^M(1-\alpha)X$. Therefore, we have:

$$\frac{L^S}{L^M} = \frac{\alpha}{1-\alpha}\frac{e^S}{e^M} \tag{B.11}$$

and

$$d\ln\left(\frac{L^S}{L^M}\right) = d\ln\left(\frac{e^S}{e^M}\right) \tag{B.12}$$

Equation (B.12) implies that, in the simple model, service employment expands because task creation and reassignment raise the labor required per dollar of service output relative to manufacturing, not because expenditure moves toward services.

B.1 Comparison with Katz and Murphy (1992)

In the canonical model of skill-biased technical change (Katz and Murphy 1992), the change in skill premium satisfies:

$$d\ln\left(\frac{w_c}{w_\ell}\right) = -\frac{1}{\sigma^K} d\ln\left(\frac{L_c}{L_\ell}\right) + \frac{\sigma^K - 1}{\sigma^K} d\ln\left(\frac{A_c}{A_\ell}\right) \tag{B.13}$$

where σ^K is the elasticity of substitution between college and non-college labor, and A_c/A_ℓ is a reduced-form relative factor-augmenting technology term. Katz and Murphy (1992) apply this framework to interpret the evolution of the U.S. college wage premium, finding sustained growth in relative demand for college workers from skill-biased technical changes.

Comparing equations (B.9) and (B.13), we find that the skill-biased technical change corresponds to the following terms:

$$\underbrace{\frac{\lambda_c^S - \lambda_c^M}{\pi_c(1-\pi_c)} dv^S}_{\text{between-sector demand shift}} + \underbrace{\frac{v^S\, d\lambda_c^S + v^M\, d\lambda_c^M}{\pi_c(1-\pi_c)}}_{\text{within-sector demand shift}} . \tag{B.14}$$

Katz and Murphy (1992) summarize changes in relative skill demand by A_c/A_ℓ. Our task expansion setting therefore provides a microfoundation for the reduced-form relative-demand shifters. An increase in J introduces tasks in which college workers have comparative advantage, while the resulting wage adjustment changes the assignment of incumbent tasks through j^*. Relative skill demand is thus jointly determined by task creation, task assignment, and sectoral reallocation.

B.2 Comparison with Buera et al. (2022)

We first present a parsimonious representation of the skill-biased structural change in Buera et al. (2022). We then show how our task-based model extends this mechanism by endogenizing the task content, skill intensity, and labor intensity of sectoral production.

Skill-Biased Structural Change. Sector $k \in \{M, S\}$ produces value added using college and non-college labor:

$$q^k = A^k \left[\alpha^k \left(L_c^k \right)^{\frac{\sigma^B - 1}{\sigma^B}} + (1 - \alpha^k) \left(L_\ell^k \right)^{\frac{\sigma^B - 1}{\sigma^B}} \right]^{\frac{\sigma^B}{\sigma^B - 1}}, \tag{B.15}$$

where A^k is sector-specific and skill-neutral productivity; σ^B is the elasticity of substitution between college and non-college workers; and α^k controls the relative demand for college labor. High-skill services are more skill-intensive when $\alpha^S > \alpha^M$.

Under CES final demand and fixed preference weights,

$$d \log \left(\frac{v^S}{1 - v^S} \right) = (1 - \sigma)\, d \log \left(\frac{p^S}{p^M} \right), \tag{B.16}$$

where σ is the elasticity of substitution between manufacturing and services in consumption. When $\sigma < 1$, an increase in the relative price of services raises their nominal value-added share. Sector-specific productivity growth can generate structural transformation by changing unit costs and hence relative prices.

Since high-skill services are more skill-intensive than manufacturing, we have $\lambda_c^S > \lambda_c^M$ in equation (B.9). Therefore, rise in the value-added share ($dv^S > 0$) increases the aggregate demand for college labor. Given relative skill supply (L_c/L_ℓ) and conditional on sectoral skill intensities ($d\lambda_c^k = 0$), this raises the college wage premium:

$$d \log \left(\frac{w_c}{w_\ell} \right) \Bigg|_{\text{BK}} = \frac{\lambda_c^S - \lambda_c^M}{\pi_c (1 - \pi_c)}\, dv^S > 0. \tag{B.17}$$

Buera et al. (2022) show that development systematically reallocates value-added toward high-skill (college) intensive sectors ($dv^S > 0$) and that this structural transformation raises relative skill demand, even when the underlying sector-specific technical change (A^k) is skill neutral.

Task-Based Model. In the model above, skill-biased structural change operates through the reallocation of value added across sectors with different skill intensities. In our framework, we endogenize these skill intensities. The college-labor share in manufacturing depends on the task threshold and relative task prices, while the college-labor share in services also depends directly on the task frontier: $\lambda_c^M = \lambda_c^M(j^*, \omega)$ and $\lambda_c^S = \lambda_c^S(j^*, \omega, J)$, where $\omega = w_\ell / w_c$. Then, the change in the college share of service value added is given by

$$d\lambda_c^S = \lambda_{c,J}^S \, dJ + \lambda_{c,j^*}^S \, dj^* + \lambda_{c,\omega}^S \, d\omega, \tag{B.18}$$

where, on the right-hand side, the first term captures the effect of new frontier tasks (dJ), the second term captures the reassignment of incumbent tasks, and the last term reflects the change in relative task prices. Analogously, for the manufacturing sector,

$$d\lambda_c^M = \lambda_{c,j^*}^M \, dj^* + \lambda_{c,\omega}^M \, d\omega. \tag{B.19}$$

where we have no direct effect on the task frontier.

When we substitute equations (B.18) and (B.19) into equation (B.9), we obtain:

$$\begin{aligned} d\log\left(\frac{w_c}{w_\ell}\right) = & -d\log\left(\frac{L_c}{L_\ell}\right) + \frac{\lambda_c^S - \lambda_c^M}{\pi_c(1-\pi_c)} \, dv^S + \frac{v^S \lambda_{c,J}^S}{\pi_c(1-\pi_c)} dJ \\ & + \frac{v^S \lambda_{c,j^*}^S + (1-v^S)\lambda_{c,j^*}^M}{\pi_c(1-\pi_c)} dj^* + \frac{v^S \lambda_{c,\omega}^S + (1-v^S)\lambda_{c,\omega}^M}{\pi_c(1-\pi_c)} d\omega. \end{aligned} \tag{B.20}$$

Equation (B.20) presents different channels determining the college wage premium. On the right-hand side, the second term captures the channel emphasized by skill-biased structural change as in (B.17). The third term is the direct effect of creating skill-intensive frontier tasks. The fourth term captures the endogenous reassignment of incumbent tasks, and the last term is adjustment in relative task prices. Note that the last term is itself endogenous to the college wage premium, so it captures the general equilibrium effects. Therefore, in the task-based model, we have the skill-biased structural change channel as in Buera et al. (2022), but with endogenous sectoral skill intensity. Expansion of the task frontier, J, can jointly change the skill intensity of services, the assignment of incumbent tasks, and the college wage premium.

The two frameworks differ in the source of sectoral reallocation. In the skill-biased structural change model, sector-specific neutral productivity growth changes relative prices and reallocates nominal value added toward a sector with greater demand for college labor, as shown in (B.16). The structural transformation then raises the college wage premium (see equation (B.17)). In our model, a change in the task frontier (J) is a common source of structural transformation and relative skill demand. The change affects the service price and hence v^S. It also changes the set of tasks performed in services, the assignment of incumbent tasks, and the labor required per dollar of service value added (e^S). Consequently, J can affect employment share in terms of (B.12). Our framework therefore provides a micro foundation for why the expanding service sector is skill intensive and why its skill and labor intensities change as the sector expands.

B.3 Comparison with Acemoglu and Restrepo (2020)

Acemoglu and Restrepo (2020) extend the canonical model of skill-biased technical change by allowing technology to change the allocation of tasks across capital, skilled labor, and unskilled labor.

Task Content and the Skill Premium. Final output is a CES aggregate of a continuum of tasks. Each task is assigned to the factor that can perform it at the lowest unit cost. Let H and L denote the supplies of skilled and unskilled labor, and let A_H and A_L denote their factor-augmenting productivities. In the framework the change in the skill premium can be written as

$$d\ln\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma}d\ln\left(\frac{H}{L}\right) + \frac{\sigma-1}{\sigma}d\ln\left(\frac{A_H}{A_L}\right) + \frac{1}{\lambda}\,d\ln\left(\frac{\Omega_H}{\Omega_L}\right)\Big|_{A_H H/A_L L}, \tag{B.21}$$

where σ is the elasticity of substitution between skilled and unskilled labor, λ is the elasticity of substitution across tasks, and Ω_H and Ω_L are productivity-weighted measures of the tasks assigned to skilled and unskilled labor.

On the right-hand side, the first two terms in equation (B.21) captures the analogous supply-and-demand channel in equation (B.13). The final term holds relative effective labor supplies fixed and captures technological changes that alter the task content of production. Technology can change relative wages by expanding or contracting the set of tasks assigned to a factor, even without changing that factor's productivity in every task. This distinction accommodates both automation and new-task creation. Automation transfers tasks previously performed by labor to capital and can reduce the wages of displaced workers. New tasks expand the productive domain of labor. Their effect on inequality depends on comparative advantage: new tasks raise the skill premium when skilled workers perform them and reduce it when unskilled workers perform them. New task creation is therefore not inherently skill-biased in their general framework.

Our Model. Our theoretical framework is designed around a different empirical question. Acemoglu and Restrepo (2020) develop a general framework for automation and new-task creation across labor and capital. Our empirical evidence concerns the local creation and adoption of new tasks in high-skill services and their relationship to universities. We therefore abstract from automation and focus on how the range of service tasks expands and how those tasks are allocated between college and non-college workers.

In our model, a change in the relative task content of services can be decomposed as

$$d \ln \left(\frac{\Omega_c}{\Omega_\ell} \right) = \frac{\partial \ln \Omega_c}{\partial J} \, dJ + \left(\frac{\partial \ln \Omega_c}{\partial j^*} - \frac{\partial \ln \Omega_\ell}{\partial j^*} \right) dj^* + \left(\frac{\partial \ln \Omega_c}{\partial \omega} - \frac{\partial \ln \Omega_\ell}{\partial \omega} \right) d\omega. \tag{B.22}$$

In the first term, an increase in J introduces tasks assigned to college labor and raises their relative task share. The second and third terms are equilibrium responses. The increase in college labor demand raises the college wage, which shifts j^* and reallocates some incumbent tasks toward non-college workers.

The distinction from Acemoglu and Restrepo (2020) is that task creation in our model is sector-specific. Manufacturing uses a fixed task set, whereas high-skill services use the interval $[0, J]$. An expansion of J therefore affects not only relative wages and task assignment, but also the scale, skill intensity, and labor intensity of high-skill services. In equation (B.20), the second line is the counterpart of the task-content terms in equation (B.21). Task-frontier expansion therefore changes the college wage premium through both the task content of services and the reallocation of value added across sectors.

In a nutshell, our model shares common features with Acemoglu and Restrepo (2020), such as the presence of new tasks and endogenous task assignment. However, our model differs from theirs in three ways. First, the primary technological shock in Acemoglu and Restrepo (2020) can be automation, which transfers tasks from labor to capital, or new-task creation, which expands the set of labor tasks. We abstract from automation and focus on the creation and adoption of new tasks that are mostly used in the high-skill service sector. Second, new tasks can favor either skilled or unskilled labor in their general framework. In our model, tasks are ordered by complexity and college workers have comparative advantage at the frontier tasks. Task expansion is therefore a skill-intensive new-task shock. Third, our model embeds task creation in a two-sector economy to study structural transformation and its geographic distribution, rather than task displacement alone. The expansion of the frontier task affects sectoral value added and employment as well as relative wages, and universities provide an institutional source of regional variation in this frontier.

B.4 Relative Price and Measured Productivity

In our model, relative prices and measured labor productivity respond to the set and assignment of tasks. Taking the derivative of the manufacturing price with respect to J,

$$\frac{d\ln p^M}{dJ} = j^* \frac{d\ln w_\ell}{dJ} + (1-j^*)\frac{d\ln w_c}{dJ} \tag{B.23}$$

For services, we obtain:

$$\frac{d\ln p^S}{dJ} = f_F + (1-\lambda_c^S)\frac{d\ln w_\ell}{dJ} + \lambda_c^S \frac{d\ln w_c}{dJ} \tag{B.24}$$

where λ_c^S is the college labor share of service costs and $f_F = \frac{w_c}{\varphi_J z_{cJ}} \frac{1}{P^S}$ is the frontier task cost share. Combining equations (B.23) and (B.24) yields:

$$\frac{d}{dJ}\ln\left(\frac{p^S}{p^M}\right) = f_F + \left[\lambda_c^S - (1-j^*)\right]\frac{d\ln w_c}{dJ} + \left[(1-\lambda_c^S) - j^*\right]\frac{d\ln w_\ell}{dJ} \tag{B.25}$$

Task frontier expansion affects the relative price through the direct cost of the new frontier task and through equilibrium wage changes. When these tasks are sufficiently skill-intensive, $\lambda_c^S > 1 - j^*$, task creation raises the relative price of services.

The measured labor productivity also depends on the task composition. In manufacturing,

$$\frac{q^M}{L^M} = \frac{1}{\int_0^{j^*} \frac{1}{z_{\ell j}} dj + \int_{j^*}^1 \frac{1}{z_{cj}} dj}, \tag{B.26}$$

For the services, we have:

$$\frac{q^S}{L^S} = \frac{1}{\int_0^{j^*} \frac{1}{\varphi_j z_{\ell j}} dj + \int_{j^*}^J \frac{1}{\varphi_j z_{cj}} dj} \tag{B.27}$$

Even when task-level productivities are fixed, measured sectoral productivity changes because a change in j^* reallocates tasks across worker types and J changes the range of tasks used in services. Task expansion raises service labor requirements, and the induced reassignment of incumbent tasks changes labor requirements in both sectors. As such, what appears in sectoral data as relative productivity growth may therefore partly reflect changes in task composition independent of exogenous relative sectoral productivity growth.

C A Microfoundation for the Regional Task Frontier

This appendix provides a microfoundation for the reduced-form relationship between universities and the task frontier discussed in Section 4.2. In particular we establish how universities affect the equilibrium adopted frontier. We interpret the task frontier as a long-lived capability chosen by headquarters (owners) before production begins. Developing this capability requires investments in knowledge, production routines, and complementary technologies. Once a task menu has been adopted, production takes it as given and use all tasks within the adopted set. The headquarters' decision and production occur sequentially. First, headquarters choose the task frontier and incur the associated sunk cost. Second, conditional on the chosen frontier, firms purchase task inputs and produce services. The adoption problem introduced in this section rationalizes the equilibrium task frontier that firms in the production stage take as given.

Available Tasks. We first define the set of available tasks in each region. Let

$$\bar{J}_n = \mathcal{J}\left(A_n^R, U_n\right) \tag{C.1}$$

denote the frontier of tasks locally available to service firms, where A_n^R captures regional innovation fundamentals and U_n measures university presence and quality. Naturally, we assume that the set of available tasks is strictly increasing in innovation fundamentals ($\mathcal{J}_A > 0$) and university elements ($\mathcal{J}_U > 0$). This formulation captures the role of university research in generating, adapting, and diffusing knowledge relevant to the local economy. It does not require that every locally available task is adopted in equilibrium.

Production Conditional on the Task Architecture. Consider a high-skill-service organization in region n. Before production, headquarters choose a task frontier J. Once the task set has been determined, all operating units of firms use tasks on the interval $[0, J]$ in production. Conditional on J, service production in period t is given by:

$$Y_{nt}^S = A_{nt}^S \left[\int_0^J \left(x_{jnt}^S\right)^{\frac{\varepsilon-1}{\varepsilon}} dj \right]^{\frac{\varepsilon}{\varepsilon-1}}, \qquad 0 < \varepsilon < 1, \tag{B.1}$$

where x_{jnt}^S is the input of task j and A_{nt}^S denotes service productivity associated with the adopted task menu. Conditional on the adopted task frontier, cost minimization implies the variable unit cost

$$c_{nt}^S = \frac{\varsigma_{nt}}{A_{nt}^S}, \qquad \varsigma_{nt} = \left[\int_0^J \gamma_{jnt}^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}}. \tag{C.2}$$

Sunk Implementation Costs. Expanding the task frontier requires headquarters to build the capacity to use a broader set of tasks. Let $\Omega_n(J; U_n, A_n^R)$ denote the sunk cost of implementation required to use task menu $[0, J]$. The cost depends on university presence and quality U_n

and other regional innovation fundamentals A_n^R. Intuitively, the cost includes expenditure to acquire knowledge and develop new production processes. Implementing higher-indexed tasks is increasingly costly, so we assume:

$$\frac{d\Omega_n}{dJ} > 0, \qquad \frac{d^2\Omega_n}{dJ^2} > 0. \tag{C.3}$$

Universities lower the marginal cost of implementing frontier tasks through access to specialized researchers and graduates, laboratories, knowledge transfer, university–industry collaboration, and opportunities for experimentation. Therefore, we suppose that the sunk cost function satisfies:

$$\frac{\partial}{\partial U_n}\frac{d\Omega_n}{dJ} < 0, \qquad \frac{\partial}{\partial A_n^R}\frac{d\Omega_n}{dJ} < 0. \tag{C.4}$$

The Headquarters Problem. Headquarters choose a long-lived task set before production. Let $\rho \in (0,1)$ denote the discount factor and let $\{y_{nt}^e\}_{t=0}^{\infty}$ denote the output path anticipated by headquarters at the time of adoption. Headquarters solves

$$J_n^* \in \arg\min_{0\leq J\leq \bar{J}_n} \Omega_n(J; U_n, A_n^R) + \mathbb{E}_0\left[\sum_{t=0}^{\infty}\rho^t y_{nt}^e c_{nt}^S\right]. \tag{C.5}$$

The trade-off is the sunk cost of implementing additional tasks against the present value of the resulting operating-cost savings.

At an interior solution, the optimal task frontier satisfies

$$-\mathbb{E}_0\left[\sum_{t=0}^{\infty}\rho^t y_{nt}^e \frac{\partial c_{nt}^S(J_n^*)}{\partial J}\right] = \frac{d}{dJ}\Omega_n(J_n^*; U_n, A_n^R) + \varpi \tag{C.6}$$

The left-hand side is the present value of the marginal reduction in future production costs from expanding the task set, while the right-hand side is the marginal sunk cost and Lagrangian multiplier associated with the task constraint ($J \leq \bar{J}_n$). Suppose $\varpi = 0$. Using equation (C.2), the first-order condition can be written as

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t y_{nt}^e \frac{c_{nt}^S}{J_n^*}\left(\left.\frac{d\log A_{nt}^S}{d\log J}\right|_{J=J_n^*} - \left.\frac{d\log \varsigma_{nt}}{d\log J}\right|_{J=J_n^*}\right)\right] = \frac{d}{dJ}\Omega_n(J_n^*; U_n, A_n^R). \tag{C.7}$$

This condition shows that headquarters expands the task frontier until the present value of the net benefit from an additional task equals its marginal cost of adoption.

Assumption C.1. *The left-hand side of equation (C.7) is continuous, monotone and either (i) decreasing or (ii) increasing and concave.*

Under Assumption C.1, the headquarters problem has a unique solution since the right-hand side of equation (C.7) is strictly increasing in J_n given (C.3). We let J_n^* denote the solution to equation (C.7). Then, the equilibrium adopted frontier is given by:

$$J_n = \min\left\{J_n^*, \bar{J}(A_n^R, U_n)\right\}, \tag{C.8}$$

and this implies

$$\frac{\partial J_n}{\partial U_n} \geq 0. \tag{C.9}$$

This follows because the marginal increase in adoption costs is low for higher U_n, as in (C.4).

Aggregation and High-Skill Service Production. Since service firms within region n face the same task prices, productivity, adoption costs, and expected market conditions, they solve the same problem as in (C.5). Therefore all firms choose the same task frontier in a symmetric equilibrium. The common frontier can consequently be represented as a region-level task frontier in production of high-skill services.

Once headquarters have selected J_n, the adoption cost is sunk. Operating units of high-skill service firms take the common task menu as given and choose task inputs to minimize variable production costs. Perfect competition and constant returns in the production technology imply $P_{nt}^S = c_{nt}^S$. Operating units therefore earn zero operating profits.

The headquarters problem is intended to rationalize the choice of a long-lived organizational technology. It does not model the financing or recovery of the sunk implementation expenditure. Equivalently, headquarters can be interpreted as acting on behalf of the owner of organizational capital, with the associated investment returns and consumption outside of the modeled regional household sector. This assumption is analogous to absentee ownership of other fixed assets and ensures that organizational rents do not enter local expenditure or housing demand.

D Model Inversion

D.1 Set Parameters and Functional Forms

Table D.1 summarizes the parameter values. The first column lists each parameter; the second column contains the corresponding notation; the third column gives its value; and the fourth column summarizes the source for the calibrated value. In addition, we assume that the task performance of each type is as follows:

$$z_{\ell j} = e^{-\theta_\ell j}, \quad z_{cj} = e^{-\theta_c j} \tag{D.1}$$

where $\theta_\ell > \theta_c > 0$. Only the relative slopes of the task-productivity schedule matter for assignment, so we normalize $\theta_\ell = 1$ and set $\theta_c = 0.5$ as a baseline.

Table D.1: Parameter values and sources

Parameter	Notation	Value	Source
Elasticity of substitution between tasks	ε	0.5	Humlum (2019)
Expenditure share on residential floor space			
— of college graduates	$1-\mu_c$	0.4	Diamond (2016)
— of non-college workers	$1-\mu_\ell$	0.4	
Elasticity of substitution across sectors	σ	0.5	
Elasticity of substitution between manufacturing goods	β	4	Feenstra et al. (2018)
Fréchet shape parameter of idiosyncratic preferences	κ	2	Fajgelbaum et al. (2019)

D.2 Inversion of Task Assignment and Task Frontier

For each region n and period t, define the observed college-to-non-college wage-bill ratios in manufacturing and high-skill services as: $R^M_{nt} = \frac{w_{cnt}L^M_{cnt}}{w_{\ell nt}L^M_{\ell nt}}$ and $R^S_{nt} = \frac{w_{cnt}L^S_{cnt}}{w_{\ell nt}L^S_{\ell nt}}$. The two ratios identify the task threshold and task frontier sequentially. Manufacturing uses the fixed task interval $[0,1]$, so R^M_{nt} depends on the assignment threshold j^*_{nt} but not on the frontier. High-skill services use tasks over $[0, J_{nt}]$. Thus conditional on j^*_{nt}, R^S_{nt} identifies J_{nt}. Observed relative wages and the assignment condition then recover relative college productivity.

Cost minimization implies that sector k's wage bill for a worker type equals that worker type's share of the sectoral task cost. Consequently, the manufacturing wage-bill ratio satisfies:

$$R^M_{nt} = \left(\frac{w_{cnt}}{w_{\ell nt}}\right)^{1-\varepsilon}\left(\frac{a_{cnt}}{a_{\ell nt}}\right)^{\varepsilon-1}\frac{\int_{j^*_{nt}}^{1} z_{cj}^{\varepsilon-1}dj}{\int_0^{j^*_{nt}} z_{\ell j}^{\varepsilon-1}dj}, \tag{D.2}$$

and the service wage-bill ratio is:

$$R^S_{nt} = \left(\frac{w_{cnt}}{w_{\ell nt}}\right)^{1-\varepsilon}\left(\frac{a_{cnt}}{a_{\ell nt}}\right)^{\varepsilon-1}\frac{\int_{j^*_{nt}}^{J_{nt}} z_{cj}^{\varepsilon-1}dj}{\int_0^{j^*_{nt}} z_{\ell j}^{\varepsilon-1}dj} \tag{D.3}$$

At the task assignment threshold, college and non-college workers have the same unit cost, so that:

$$\frac{w_{cnt}}{w_{\ell nt}} = \frac{a_{cnt}}{a_{\ell nt}}\frac{z_{cj^*_{nt}}}{z_{\ell j^*_{nt}}} \tag{D.4}$$

Substituting (D.4) into the wage-bill ratios (D.2) and (D.3) eliminates both observed relative wages and relative worker productivity:

$$R^M_{nt} = \left(\frac{z_{cj^*_{nt}}}{z_{\ell j^*_{nt}}}\right)^{1-\varepsilon}\frac{\int_{j^*_{nt}}^{1} z_{cj}^{\varepsilon-1}dj}{\int_0^{j^*_{nt}} z_{\ell j}^{\varepsilon-1}dj}, \tag{D.5}$$

$$R_{nt}^{S}=\left(\frac{z_{cj_{nt}^{*}}}{z_{\ell j_{nt}^{*}}}\right)^{1-\varepsilon}\frac{\int_{j_{nt}^{*}}^{J_{nt}}z_{cj}^{\varepsilon-1}dj}{\int_{0}^{j_{nt}^{*}}z_{\ell j}^{\varepsilon-1}dj} \tag{D.6}$$

Equation (D.5) identifies j_{nt}^{*} from the manufacturing wage-bill ratio, R_{nt}^{M}. Conditional on the threshold, equation (D.6) identifies J_{nt} from the service wage-bill ratio, R_{nt}^{S}. Importantly, this inversion does not require sectoral productivity or demand conditions.

Under the parametrization (D.1), equations (D.5) and (D.6) lead to:

$$\ln R_{nt}^{M}=(1-\varepsilon)(\theta_{\ell}-\theta_{c})j_{nt}^{*}+\ln\left[\frac{\theta_{\ell}}{\theta_{c}}\frac{e^{(1-\varepsilon)\theta_{c}}-e^{(1-\varepsilon)\theta_{c}j_{nt}^{*}}}{e^{(1-\varepsilon)\theta_{\ell}j_{nt}^{*}}-1}\right] \tag{D.7}$$

and

$$\ln R_{nt}^{S}=(1-\varepsilon)(\theta_{\ell}-\theta_{c})j_{nt}^{*}+\ln\left[\frac{\theta_{\ell}}{\theta_{c}}\frac{e^{(1-\varepsilon)\theta_{c}J_{nt}}-e^{(1-\varepsilon)\theta_{c}j_{nt}^{*}}}{e^{(1-\varepsilon)\theta_{\ell}j_{nt}^{*}}-1}\right] \tag{D.8}$$

These two equations are solved sequentially rather than jointly. We first recover j_{nt}^{*} from equation (D.7) and then recover J_{nt} from equation (D.8).

Lastly, relative college productivity follows from equation (D.4):

$$\ln\left(\frac{w_{cnt}}{w_{\ell nt}}\right)=\ln\left(\frac{a_{cnt}}{a_{\ell nt}}\right)+(\theta_{\ell}-\theta_{c})j_{nt}^{*} \tag{D.9}$$

The next proposition ensures the existence and uniqueness of the solution.

Proposition D.1 (Uniqueness of j_{nt}^{*}). *Suppose parameters satisfy $0<\varepsilon<1$ and $\theta_{\ell}>\theta_{c}>0$. If*

$$\theta_{\ell}-\theta_{c}<\frac{\theta_{c}}{e^{\theta_{c}(1-\varepsilon)}-1}+\frac{\theta_{\ell}}{1-e^{-\theta_{\ell}(1-\varepsilon)}}, \tag{D.10}$$

then equations (D.7) and (D.8) admit a unique solution (j_{nt}^{*},J_{nt}) satisfying $0<j_{nt}^{*}<1<J_{nt}$.

Proof. Define $f(j)\equiv(1-\varepsilon)(\theta_{\ell}-\theta_{c})j+\ln\left(\frac{e^{\theta_{c}(1-\varepsilon)}-e^{\theta_{c}(1-\varepsilon)j}}{e^{\theta_{\ell}(1-\varepsilon)j}-1}\right)$ for $j\in(0,1)$. The function $f(\cdot)$ is continuous on $(0,1)$ and satisfies $\lim_{j\to0^{+}}f(j)=+\infty$ and $\lim_{j\to1^{-}}f(j)=-\infty$. Hence a solution $j_{nt}^{*}\in(0,1)$ exists. Differentiating, $f'(j)=(1-\varepsilon)(\theta_{\ell}-\theta_{c})-\frac{\theta_{c}(1-\varepsilon)e^{\theta_{c}(1-\varepsilon)j}}{e^{\theta_{c}(1-\varepsilon)}-e^{\theta_{c}(1-\varepsilon)j}}-\frac{\theta_{\ell}(1-\varepsilon)e^{\theta_{\ell}(1-\varepsilon)j}}{e^{\theta_{\ell}(1-\varepsilon)j}-1}$. Condition (D.10) ensures that $f'(j)<0$ on $(0,1)$. Therefore, $f(\cdot)$ is strictly decreasing and the solution j_{nt}^{*} is unique. Given j_{nt}^{*}, define $\bar{c}\equiv e^{\theta_{\ell}(1-\varepsilon)j_{nt}^{*}}$ and $g(J)\equiv\ln\left(\frac{e^{\theta_{\ell}(1-\varepsilon)J}-\bar{c}}{\bar{c}-1}\right)$ for $J>1$. The function $g(\cdot)$ is continuous and strictly increasing on $(1,\infty)$, $\lim_{J\to1^{+}}g(J)=-\infty$ and $\lim_{J\to+\infty}g(J)=+\infty$. Hence there exists a unique $J_{nt}>1$ solving equation (D.8). □

D.3 Recovery of Regional Fundamentals

Prices. Goods price are:

$$\left(p_{nt}^{M}\right)^{1-\varepsilon}=\left(A_{nt}^{M}\right)^{\varepsilon-1}\int_{0}^{1}\gamma_{jn}^{1-\varepsilon}dj=\left(a_{\ell nt}A_{nt}^{M}\right)^{\varepsilon-1}\mathrm{W}_{nt}^{1-\varepsilon} \tag{D.11}$$

where

$$\mathbb{W}_{nt} = \left[\frac{w_{\ell nt}^{1-\varepsilon}}{\theta_\ell(1-\varepsilon)} \left(e^{\theta_\ell(1-\varepsilon) j_{nt}^*} - 1 \right) + \left(\frac{a_{cnt}}{a_{\ell nt}} \right)^{\varepsilon - 1} \frac{w_{cnt}^{1-\varepsilon}}{\theta_c(1-\varepsilon)} \left(e^{\theta_c(1-\varepsilon)} - e^{\theta_c(1-\varepsilon) j_{nt}^*} \right) \right]^{\frac{1}{1-\varepsilon}} \tag{D.12}$$

Then, price of manufacturing goods produced in n is:

$$p_{nt}^M = \frac{\mathbb{W}_{nt}}{a_{\ell nt} A_{nt}^M} \tag{D.13}$$

Analogously, the price for high-skill service is:

$$P_{nt}^S = \frac{\mathbb{C}_{nt}}{a_{\ell nt} A_{nt}^S} \tag{D.14}$$

where we define:

$$\mathbb{C}_{nt} \equiv \left[\frac{w_{\ell nt}^{1-\varepsilon}}{\theta_\ell(1-\varepsilon)} \left(e^{\theta_\ell(1-\varepsilon) j_{nt}^*} - 1 \right) + \left(\frac{a_{cnt}}{a_{\ell nt}} \right)^{\varepsilon - 1} \frac{w_{cnt}^{1-\varepsilon}}{\theta_c(1-\varepsilon)} \left(e^{\theta_c(1-\varepsilon) J_{nt}} - e^{\theta_c(1-\varepsilon) j_{nt}^*} \right) \right]^{\frac{1}{1-\varepsilon}}. \tag{D.15}$$

Next, expenditure shares on manufacturing and services are:

$$\xi_{nt}^{\mathrm{M}} = \frac{\left(\widetilde{P}_{nt}^S\right)^{1-\sigma}}{\left(\widetilde{P}_t^M\right)^{1-\sigma} + \left(\widetilde{P}_{nt}^S\right)^{1-\sigma}}, \quad \xi_{nt}^{\mathrm{S}} = \frac{\left(\widetilde{P}_{nt}^S\right)^{1-\sigma}}{\left(\widetilde{P}_t^M\right)^{1-\sigma} + \left(\widetilde{P}_{nt}^S\right)^{1-\sigma}}, \tag{D.16}$$

where we refer $\widetilde{P}_{nt}^k = P_{nt}^k / \alpha_t^k$ refer to the price index adjusted by taste shifter. In the following, we consider the inversion of the adjusted productivity:

$$\widetilde{A}_{nt}^M = \alpha_t^{\mathrm{M}} a_{\ell nt} A_{nt}^M, \quad \widetilde{A}_{nt}^S = \alpha_t^{\mathrm{S}} a_{\ell nt} A_{nt}^S. \tag{D.17}$$

Manufacturing Productivity. Trade equation for manufacturing implies:

$$X_{nt}^{\mathrm{M}} = \frac{\left(p_{nt}^M\right)^{1-\beta}}{\sum_{n'=1}^N \left(p_{n't}^M\right)^{1-\beta}} \mathbb{X}^{\mathrm{M}}, \tag{D.18}$$

where $X_{nt}^{\mathrm{M}} = w_{cnt} L_{cnt}^{\mathrm{M}} + w_{\ell nt} L_{\ell nt}^{\mathrm{M}}$ and $\mathbb{X}^{\mathrm{M}}$ is total demand for manufactuing goods. Rearranging the equations and using adjusted productivity, $\widetilde{A}_{nt}^M$, we obtain:

$$\frac{X_{nt}^M}{\sum_{n'=1}^N X_{n't}^M} = \frac{\left(\frac{\mathbb{W}_{nt}}{\widetilde{A}_{nt}^M}\right)^{1-\beta}}{\sum_{n'=1}^N \left(\frac{\mathbb{W}_{n't}}{\widetilde{A}_{n't}^M}\right)^{1-\beta}} \tag{D.19}$$

There exists a unique (up-to-scale) vector, $\widetilde{A}_{nt}^M$, which solves equation (D.19) conditional on (w_{int}, X_{nt}^M, $\mathbb{W}_{nt}$).[D.1] Using the productivity, we can derive the adjusted manufacturing price index:

$$\widetilde{P}_t^M = \left[\sum_{n=1}^N \left(\frac{\mathbb{W}_{nt}}{\widetilde{A}_{nt}^M} \right)^{1-\beta} \right]^{\frac{1}{1-\beta}} \tag{D.20}$$

[D.1] Equation (D.19) is homogeneous of degree zero in $\{\widetilde{A}_{nt}^M\}$. This implies that, for each location, $\{\widetilde{A}_{nt}^M\}$ is only identified up to a common scale. Suppose that there exist two linearly independent vectors $\widetilde{A}_{nt}$ and $\widetilde{A}_{nt}^{M'}$ solving the system

High-skill Service Productivity. Using the adjusted prices of high-skill services, $\widetilde{P}^S_{nt} \equiv P^S_{nt}/\alpha^S_t = \mathbb{C}_{nt}/\widetilde{A}^S_{nt}$, the zero profit for non-tradable high-skill services in region n implies:

$$w_{cnt}L^S_{cnt} + w_{\ell nt}L^S_{\ell nt} = \frac{\left(\mathbb{C}_{nt}/\widetilde{A}^S_{nt}\right)^{1-\sigma}}{\left(\widetilde{P}^M_t\right)^{1-\sigma} + \left(\mathbb{C}_{nt}/\widetilde{A}^S_{nt}\right)^{1-\sigma}}\left(\mu_c w_{cnt}L_{cnt} + \mu_\ell w_{\ell nt}L_{\ell nt}\right) \tag{D.21}$$

Solving this equation yields unique vector of adjusted high-skill service productivity:

$$\widetilde{A}^S_{nt} = \frac{\mathbb{C}_{nt}}{\left(\frac{\chi_{nt}}{1-\chi_{nt}}\right)^{\frac{1}{1-\sigma}}\widetilde{P}^M_t}, \quad \text{with} \quad \chi_{nt} = \frac{w_{cnt}L^S_{cnt} + w_{\ell nt}L^S_{\ell nt}}{\mu_c w_{cnt}L_{cnt} + \mu_\ell w_{\ell nt}L_{\ell nt}} \tag{D.22}$$

In turn, we obtain the adjusted price of high-skill services:

$$\widetilde{P}^S_{nt} = \frac{\mathbb{C}_{nt}}{\widetilde{A}^S_{nt}} = \left(\frac{\chi_{nt}}{1-\chi_{nt}}\right)^{\frac{1}{1-\sigma}}\widetilde{P}^M_t \tag{D.23}$$

Using the adjusted prices of goods ($\widetilde{P}^M_t$) and high-skill services ($\widetilde{P}^S_{nt}$), the aggregate price index is given by:

$$\mathbb{P}_{nt} = \left[\left(\widetilde{P}^M_t\right)^{1-\sigma} + \left(\widetilde{P}^S_{nt}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = \left(\frac{1}{1-\chi_{nt}}\right)^{\frac{1}{1-\sigma}}\widetilde{P}^M_t. \tag{D.24}$$

Amenities and Floor Spaces. The mobility of college graduates implies that

$$\ln\left(\frac{L_{cnt}}{\bar{L}_{ct}}\right) = \ln B_{nt} + \kappa\ln w_{cnt} - \kappa\mu_c\ln\mathbb{P}_{nt} - \kappa(1-\mu_c)\ln r_{nt} - \ln\Phi_t, \tag{D.25}$$

where $\Phi_t = \sum_{n'=1}^N B_{n't}w^\kappa_{cn't}\left(\mathbb{P}^{\mu_c}_{n't}r^{1-\mu_c}_{n't}\right)^{-\kappa}$. We subtract the average of them and normalize the geometric mean of amenities ($\frac{1}{N}\sum_{n=1}^N \ln B_{nt} = 0$) to obtain:

$$\ln B_{nt} = \left[\log\left(\frac{L_{cnt}}{\bar{L}_{ct}}\right) - \sum_{n'=1}^N \log\left(\frac{L_{cnt}}{\bar{L}_{ct}}\right)\right] - \kappa\ln\left[\frac{w_{cnt}}{\bar{w}_{ct}}\right] + \kappa\mu_c\ln\left[\frac{\mathbb{P}_{nt}}{\bar{\mathbb{P}}_t}\right] + \kappa(1-\mu_c)\ln\left[\frac{r_{nt}}{\bar{r}_t}\right], \tag{D.26}$$

where we define $\bar{\mathbb{P}}_t \equiv \left(\prod_n \mathbb{P}_{nt}\right)^{\frac{1}{N}}$ and $\bar{r}_t \equiv \left(\prod_n r_{nt}\right)^{\frac{1}{N}}$ for their geometric means.

Lastly the floor space market cleaning condition implies that the floor space endowment is:

$$H_{nt} = \frac{1}{r_{nt}}\sum_{i\in\{\ell,c\}}(1-\mu_i)w_{int}L_{int}. \tag{D.27}$$

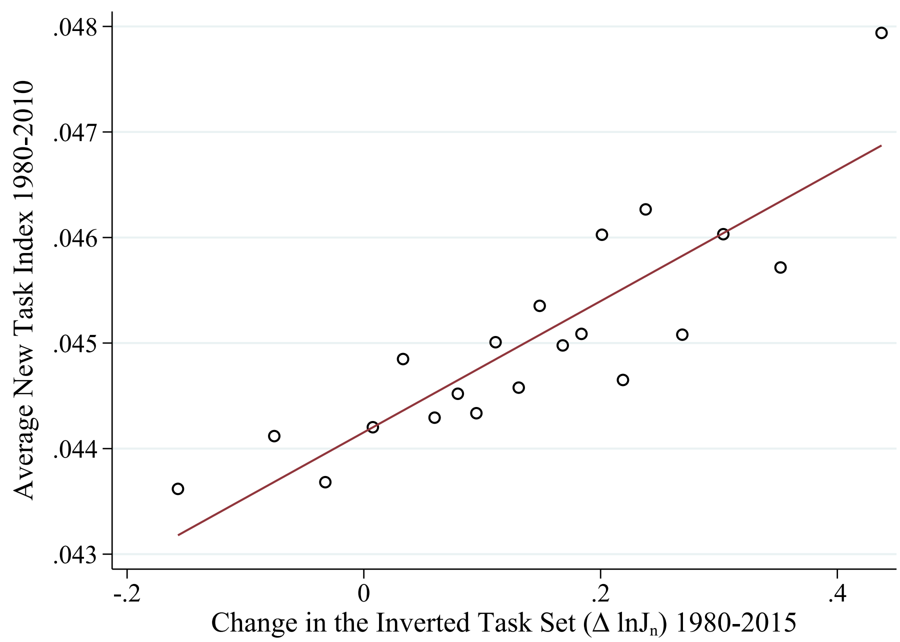
---

of equations (D.19). We let $d_n = \frac{\widetilde{A}^{M\prime}_{nt}}{\widetilde{A}^M_{nt}}$ for every element and without loss of generality we set $l = \arg\max_n d_n$. Using this, we define $\widetilde{A}^{M\prime\prime}_{nt} = d_l\widetilde{A}^M_{nt}$ and, by construction, $\widetilde{A}^{M\prime\prime}_{lt} = \widetilde{A}^{M\prime}_{lt}$ and $\widetilde{A}^{M\prime\prime}_{lt} = d_l\widetilde{A}^M_{nt} > d_n\widetilde{A}^M_{nt} = \widetilde{A}^{M\prime}_{nt}$ for other elements n. For the location l, we have: $0 = \frac{X^M_{lt}}{\sum_{n'=1}^N X^M_{n't}} - \frac{\left(\mathbb{W}_{lt}/\widetilde{A}^{M\prime}_{lt}\right)^{1-\beta}}{\sum_{n=1}^N\left(\mathbb{W}_{nt}/\widetilde{A}^{M\prime}_{nt}\right)^{1-\beta}} < \frac{X^M_{lt}}{\sum_{n'=1}^N X^M_{n't}} - \frac{\left(\mathbb{W}_{lt}/\widetilde{A}^{M\prime\prime}_{lt}\right)^{1-\beta}}{\sum_{n=1}^N\left(\mathbb{W}_{nt}/\widetilde{A}^{M\prime\prime}_{nt}\right)^{1-\beta}} = \frac{X^M_{lt}}{\sum_{n'=1}^N X^M_{n't}} - \frac{\left(\mathbb{W}_{lt}/\widetilde{A}^M_{lt}\right)^{1-\beta}}{\sum_{n=1}^N\left(\mathbb{W}_{nt}/\widetilde{A}^M_{nt}\right)^{1-\beta}}$, which leads to a contradiction.

D.4 *External Validation of the Recovered Task Frontier*

In Figure D.1 we examine the relationship between ΔJ_n and the New Task Index by controlling for initial regional characteristics, including total employment, high-skill service employment, and the employment of college workers. The resulting binscatter plot depicts the conditional relationship between the two measures and reveals an even stronger positive association.

Figure D.1: Recovered Task-Frontier Growth and Exposure to New Tasks (New Task Index)



Notes: This figure replicates Fig 6 but adds three control variables: the logarithm of total employment in 1980; the logarithm of high-skill service employment in 1980; and the logarithm of college employment in 1980.

D.5 *Universities and Recovered Task Frontier and Productivity*

Let $U_n \in \{1, 2, 3, 4, 5\}$ denote a categorical measure of university presence in region n. The lowest category, $U_n = 1$, corresponds to regions without universities or with universities ranked below the top 400, while $U_n = 5$ indicates the presence of a top-100 university. University ranking is described in Section 2.

Motivated by the reduced-form evidence in Section 2.2, we estimate the relationship between long-run changes in the task frontier and university presence using the following specification:

$$\Delta \ln J_n = \varsigma + \sum_{k \in \{1,2,3,4,5\}} \rho_k \mathbb{I}\left[U_n = k\right] + X'_{n,1980}\varrho + \epsilon_n \tag{D.28}$$

where $\Delta \ln J_n$ denotes the change in the task frontier between 1980 and 2015; ς is a constant capturing common trends; $X_{n,1980}$ is a vector of baseline regional characteristics measured in 1980; and ϵ_n is an error term. The omitted category ($U_n = 1$) serves as the baseline, so each coefficient ρ_k captures the long-run difference in task frontier growth relative to regions without or with very low-rank universities. Identification relies on cross-regional variation in university presence and ranking, holding fixed initial regional characteristics. Because universities are long-lived institutions whose locations and relative rankings change slowly over time, we interpret the coefficients as capturing persistent differences in equilibrium task expansion, rather than short-run responses to transitory shocks.

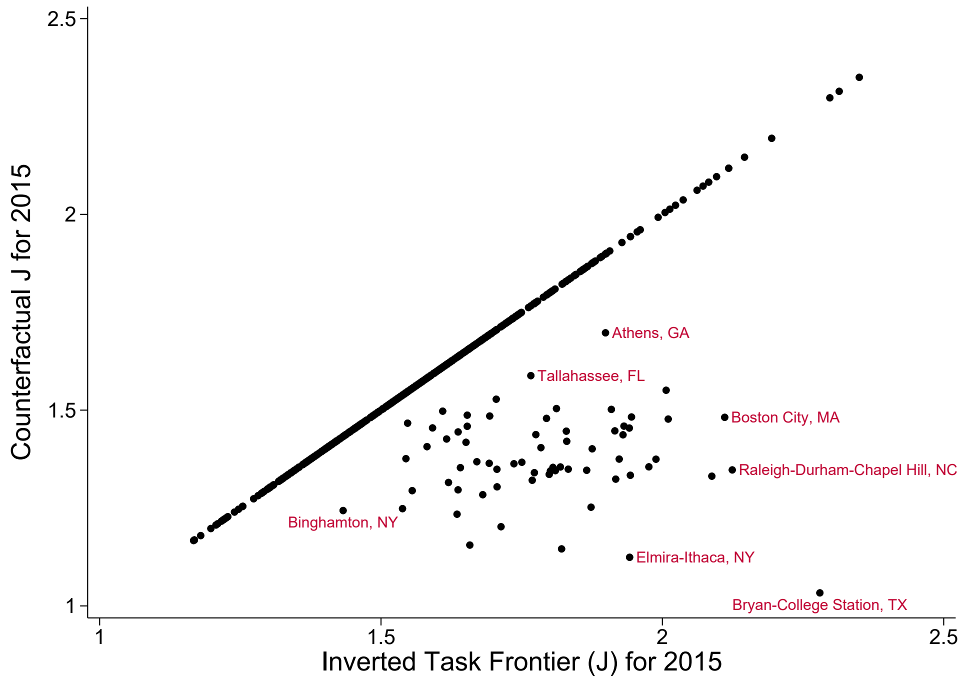
The main identification concern is that university locations may be correlated with unobserved determinants of task growth, such as latent productivity trends or historical industrial specialization. To mitigate this concern, we condition on a set of baseline controls measured in 1980, including total employment, sectoral employment shares, and college graduates. These variables proxy for initial comparative advantage and long-run growth potential. Under the identifying assumption that, conditional on these baseline characteristics, unobserved changes in task demand are orthogonal to university rank, OLS estimation of equation (D.28) identifies the effect of universities on the expansion of the task frontier.

E Counterfactual Analysis

This appendix provides additional details and the computational algorithm used in the counterfactual analysis.

We consider two scenarios. First, in the task-frontier counterfactual, we set $J_{n,15}^{\mathrm{CF}} = J_{n,80}$ for commuting zones with a top-ranked university. All other fundamentals remain unchanged. The second counterfactual simultaneously shuts down frontier task expansion and changes in relative college productivity. That is, for commuting zones with a top-ranked university, we set $J_{n,15}^{\mathrm{CF}} = J_{n,80}$ and $a_{cn,15}^{\mathrm{CF}}/a_{\ell n,15} = a_{cn,80}/a_{\ell n,80}$. Figure E.1 shows the counterfactual task frontier for commuting zones. The counterfactual exercise sets the task frontier in 2015 to its 1980 level. Therefore, commuting zones not on the 45-degree line are those treated in the counterfactual analysis. We also show names of some treated commuting zones in the figure.

Figure E.1: Counterfactual Task Frontier



Notes: This figure plots the baseline task frontier (J_n) for 2015 on the horizontal axis and its counterfactual on the vertical axis across commuting zones.

E.1 Manufacturing Absorption Adjustment

The calibration recovers manufacturing productivity from observed manufacturing wage bills: $X_{n,15}^{M,\text{Obs}} = w_{\ell n,15}L_{\ell n,15} + w_{cn,15}L_{cn,15}$. The model, however, determines aggregate manufacturing expenditure from household demand: $\bar{X}_{15}^{M} = \sum_{n=1}^{N} \xi_{n,15}^{M} Y_{n,15}$, where $Y_{n,15}$ is aggregate expenditure in n.

These two measures need not coincide. In the data, manufacturing output is not absorbed solely through household final consumption. Manufacturing output is also used as an intermediate input, government consumption, investment, and net exports. The model abstracts from these additional sources of demand. As a result, manufacturing value added used to recover productivity may differ from the manufacturing expenditure implied by the household demand system.

To reconcile the production and expenditure blocks, we introduce a manufacturing absorption factor:

$$\Xi^{M} = \frac{\sum_{n=1}^{N} X_{n,15}^{M,\text{Obs}}}{\sum_{n=1}^{N} \xi_{n,15}^{M} Y_{n,15}} \tag{E.1}$$

Aggregate manufacturing expenditure is then given by:

$$\bar{X}_{15}^{M} = \Xi^{M} \sum_{n=1}^{N} \xi_{n,15}^{M} Y_{n,15}$$

and is allocated according to the CES demand system,

$$X_{n,15}^{M} = \left(\frac{p_{n,15}^{M}}{P_{15}^{M}} \right)^{1-\beta} \bar{X}_{15}^{M}$$

The adjustment scales aggregate manufacturing absorption but leaves relative demand across regions unchanged. Therefore, it does not alter relative manufacturing prices or allocation of expenditure. Its purpose is to ensure that the baseline equilibrium reproduces observed 2015 manufacturing value added, and hence the calibrated sectoral value-added shares, before the counterfactuals are computed. We hold Ξ fixed in all counterfactuals.

E.2 Counterfactual Equilibrium Algorithm

The equilibrium is computed using a nested fixed-point algorithm. The inner loop solves for wages conditional on the spatial allocation of college workers, while the outer loop updates the regional distribution of college labor. All counterfactuals are initialized from the observed 2015 equilibrium.

Initialize Regional College Employment (Step #1). The college-worker employment is initialized at its observed 2015 distribution, $L_{cn}^{(0)} = L_{cn,15}^{\text{obs}}$. The national supply of college workers, $\bar{L}_c$ and regional distribution of non-college workers, $L_{\ell n}$, remain fixed. Conditional on the college-worker allocation $\{L_{cn}^{(q)}\}$, we solve for the equilibrium wage.

Compute Task Assignment (Step #2). For a candidate wage vector $\{w_{cn}, w_{\ell n}\}_{n=1}^{N}$, the task threshold equalizes the unit costs of college and non-college workers:

$$j_n^* = \frac{\log(w_{cn}/w_{\ell n}) - \log \zeta_n}{\theta_\ell - \theta_c}. \tag{E.2}$$

Manufacturing tasks are defined on the interval $[0, 1]$, while service tasks are defined on $[0, J_n]$. We therefore restrict the threshold j_n^* satisfying $0 < j_n^* < \min\{1, J_n\}$.[E.1]

[E.1]Numerically, we take $j_n^* = \min[\max(j_n^*, \varrho), \min(1 - \varrho, J_n - \varrho)]$ with $\varrho = 10^{-8}$. This restriction prevents task allocations from leaving the admissible task intervals.

Compute Prices (Step #3). Given wages and task allocation, manufacturing and service task-cost composites (D.12) and (D.15) are computed. Sectoral prices are:

$$p_n^M = \frac{\mathbb{W}_n}{\widetilde{A}_n^M}, \qquad P_n^S = \frac{\mathbb{C}_n}{\widetilde{A}_n^S}, \tag{E.3}$$

where we use calibrated sectoral productivity in 2015 for $\widetilde{A}_n^M$ and $\widetilde{A}_n^S$. The manufacturing price index and the local consumption price index are:

$$P^M = \left[\sum_{n=1}^{N} \left(p_n^M\right)^{1-\beta}\right]^{1/(1-\beta)}, \qquad \mathbb{P}_n = \left[(P^M)^{1-\sigma} + (P_n^S)^{1-\sigma}\right]^{1/(1-\sigma)}.$$

Compute Expenditures (Step #4). Aggregate expenditure on consumption of goods and services in n is $Y_n = \mu_c w_{cn} L_{cn} + \mu_\ell w_{\ell n} L_{\ell n}$. Service expenditure is given by:

$$X_n^S = \xi_n^S Y_n, \quad \xi_n^S = \frac{P_n^{S\,1-\sigma}}{P^{M\,1-\sigma} + P_n^{S\,1-\sigma}} \tag{E.4}$$

Let $\xi_n^M = 1 - \xi_n^S$. Aggregate manufacturing expenditure is:

$$\bar{X}^M = \Xi^M \sum_{n=1}^{N} \xi_n^M Y_n \tag{E.5}$$

where Ξ^M is the manufacturing absorption adjustment defined by (E.1). Then, regional manufacturing expenditure is allocated according to the CES demand system:

$$X_n^M = \left(\frac{p_n^M}{P^M}\right)^{1-\beta} \bar{X}^M. \tag{E.6}$$

Update Wages (Step #5). Given sectoral expenditures and task assignment, we compute the wage bills paid to each labor type in each sector. The manufacturing wage bill paid to non-college labor is

$$E_{\ell n}^M = \frac{w_{\ell n}^{1-\varepsilon}\left[e^{\theta_\ell(1-\varepsilon)j_n^*} - 1\right]}{\theta_\ell(1-\varepsilon)} \frac{X_n^M}{\mathbb{W}_n^{1-\varepsilon}} \tag{E.7}$$

The manufacturing wage bill paid to college labor is

$$E_{cn}^M = \frac{w_{cn}^{1-\varepsilon}\zeta_n^{\varepsilon-1}\left[e^{\theta_c(1-\varepsilon)} - e^{\theta_c(1-\varepsilon)j_n^*}\right]}{\theta_c(1-\varepsilon)} \frac{X_n^M}{\mathbb{W}_n^{1-\varepsilon}} \tag{E.8}$$

In turn, the service-sector wage bill paid to non-college labor is

$$E_{\ell n}^S = \frac{w_{\ell n}^{1-\varepsilon}\left[e^{\theta_\ell(1-\varepsilon)j_n^*} - 1\right]}{\theta_\ell(1-\varepsilon)} \frac{X_n^S}{\mathbb{C}_n^{1-\varepsilon}} \tag{E.9}$$

for college labor performing service tasks on $[j_n^*, J_n]$,

$$E_{cn}^S = \frac{w_{cn}^{1-\varepsilon}\zeta_n^{\varepsilon-1}\left[e^{\theta_c(1-\varepsilon)J_n} - e^{\theta_c(1-\varepsilon)j_n^*}\right]}{\theta_c(1-\varepsilon)} \frac{X_n^S}{\mathbb{C}_n^{1-\varepsilon}} \tag{E.10}$$

Total payments to each labor type are obtained by summing across sectors: $E_{\ell n} = E_{\ell n}^M + E_{\ell n}^S$ and $E_{cn} = E_{cn}^M + E_{cn}^S$. Conditional on the current employment allocation, market-clearing wages implied by factor demand are

$$w_{\ell n}^{'} = \frac{E_{\ell n}}{L_{\ell n}}, \quad w_{cn}^{'} = \frac{E_{cn}}{L_{cn}} \tag{E.11}$$

Since the equilibrium determines only relative wages, we normalize the geometric mean of non-college wages to its calibrated 2015 value. Then, we update wages using logarithmic damping,

$$\log w^{(k+1)} = \lambda_w \log w' + (1-\lambda_w) \log w^{(k)},$$

with damping parameter λ_w. Steps 2 to 5 are repeated until the wage fixed-point residual satisfies: $\max_{n=1,2,\cdots,N} |\log w_n^{'} - \log w_n| < 10^{-6}$. This completes the inner loop.

Update the Spatial Allocation of College Workers (Step #6). When housing supply H_n is fixed, housing-market clearing determines rents r_n'. Given wages, prices, rents, and amenities, the indirect utility of college workers in region n is:

$$u_{cn} = B_n w_{cn} P_n^{-\mu_c} r_n^{-(1-\mu_c)},$$

where amenities B_n are recovered in calibration and held fixed throughout the counterfactual exercises. The migration equation implies

$$L_{cn}^{'} = \frac{e^{\kappa \log u_{cn}}}{\sum_{n'=1}^{N} e^{\kappa \log u_{cn'}}} \bar{L}_c \tag{E.12}$$

Employment is updated using:

$$\log L_{cn}^{(k+1)} = \lambda_L \log L_c^{'} + (1-\lambda_L) \log L_{cn}^{(k)}$$

The updated allocation is renormalized to satisfy: $\sum_{n=1}^{N} L_{cn} = \bar{L}_c$. The migration fixed point converges when $\max_{n=1,2,\cdots,N} |\log L_{cn}^{(k+1)} - \log L_{cn}^{(k)}| < 10^{-6}$. At convergence, wages, migration decisions, prices, expenditures, and task allocation are jointly consistent. The resulting allocation is the counterfactual spatial equilibrium.

E.3 Robustness of Counterfactual Results

This section summarizes the alternative counterfactual specifications reported in Tables E.1–E.4.

Fixed Spatial Distribution of College Workers. As a robustness exercise, we also compute counterfactuals with the migration channel shut down. In this case, $L_{cn}^{\text{CF}} = L_{cn,15}$ for all regions. Step 6 in Appendix E.2 is omitted entirely, and only the wage fixed point described in Steps 2-5 is solved. Comparing migration and no-migration equilibria isolates the contribution of spatial sorting from the within-region effects of task reallocation, price adjustment, and wage determination.

Alternative Comparative Advantage Parameter (θ_c). The baseline sets $\theta_\ell = 1$ and $\theta_c = 0.5$. To see the robustness of the results to the parameter choices, we repeat the model inversion and counterfactual analysis using $\theta_c = 0.25$ and $\theta_c = 0.75$, holding the normalization $\theta_\ell = 1$ fixed. For each value of θ_c, we re-estimate the task thresholds, task frontiers, relative worker productivities, and sectoral productivities and re-compute the counterfactual equilibrium.

Productivity Gains from Task Expansion. The baseline holds service productivity fixed when the task frontier changes. We alternatively assume $A_n^S = \bar{A}_n^S J_n^\phi$ for $\phi = 0.5$ and $\phi = 1$. Under this specification, resetting J_n to its 1980 value also changes service productivity. We re-compute service prices, expenditures, labor demand, wages, rents, and worker locations in the counterfactual equilibrium, with the results shown in Table E.3 and E.4.

F Data Construction

Crosswalks and Imputation. For geographic harmonization, we map Census State Economic Areas, Census County Groups, and ACS Public Use Micro Areas to 1990 CZs using the crosswalk of Autor and Dorn (2013), which forms our baseline geographic unit. Occupational codes from the Census (occ) are mapped to the occ1990dd classification. Similarly, to ensure consistency over time, industry codes are harmonized to the 1987 four-digit Standard Industrial Classification (SIC87). Since County Business Patterns (CBP) uses different SIC and NAICS classification across years, we apply weighted industry crosswalks before aggregating employment to commuting zones. CBP suppresses employment for some county-industry pairs. Following Acemoglu et al. (2016), we impute suppressed values using establishment counts by employment-size class and impose consistency across the industry hierarchy. When employment in a parent-level industry differs from the sum of detailed industries, we use the detailed totals and allocate residual employment across the relevant subordinate industries.

Table E.1: Sensitivity Analysis for Task-Frontier Expansion in Top-University Regions and Structural Transformation

	Change in High-Skill Service					
	Value-Added Share			Employment Share		
	Top 100	Other Univ.	No Univ.	Top 100	Other Univ.	No Univ.
Observed change in 1980–2015	17.11	12.85	10.52	13.91	10.66	8.67
	(0.63)	(0.34)	(0.40)	(0.58)	(0.31)	(0.37)
(A) No Migration						
Shut down changes in J_n	11.40	10.56	8.36	10.85	8.52	6.65
	(0.57)	(0.33)	(0.39)	(0.59)	(0.30)	(0.36)
Shut down changes in J_n and $\mathbb{a}_n$	11.18	10.05	7.85	11.66	8.04	6.17
	(0.57)	(0.33)	(0.39)	(0.57)	(0.30)	(0.36)
(B.1) Set $\theta_c = 0.25$						
Shut down changes in J_n	11.59	11.09	8.88	11.19	8.40	6.59
	(0.57)	(0.33)	(0.39)	(0.59)	(0.30)	(0.36)
Shut down changes in J_n and $\mathbb{a}_n$	11.17	10.01	7.81	11.75	8.06	6.18
	(0.56)	(0.33)	(0.39)	(0.58)	(0.30)	(0.36)
(B.2) Set $\theta_c = 0.75$						
Shut down changes in J_n	11.82	11.16	8.94	11.25	8.61	6.79
	(0.57)	(0.33)	(0.39)	(0.59)	(0.30)	(0.36)
Shut down changes in J_n and $\mathbb{a}_n$	11.42	10.30	8.09	11.73	8.21	6.34
	(0.56)	(0.33)	(0.39)	(0.57)	(0.30)	(0.36)

Notes: The first three rows report mean changes from 1980 to observed or counterfactual 2015, in percentage points. Standard errors across commuting zones are reported in parentheses. The contribution of each counterfactual channel is based on the difference between the observed and counterfactual changes, and the percentage explained divides this contribution by the observed change in top-university commuting zones. "Other Univ." denotes commuting zones with a university but no top-100 institution.

Employment and Wages. Local industry employment and establishment counts are constructed from CBP for 1977−-2016. The early files are obtained from ICPSR and the later files from the US Census Bureau. After imputing suppressed observations and harmonizing industry codes, we aggregate county-industry observations to commuting zones. We also use the decennial Census and American Community Survey (ACS) to measure wages, education, occupations, and skill-specific employment. Workers with at least a college degree are classified as college workers, and all others as non-college workers. Our baseline sample includes employed individuals who worked at least 50 weeks during the previous year. Individual observations are then aggregated to the regional levels using person weights. Note that the two data sources differ in coverage: CBP records employment at the establishment level, whereas the Census and ACS are based on individual-level samples. As a result, their employment shares need not coincide in levels. Nev-

Table E.2: Sensitivity Analysis for Task-Frontier Expansion in Top-University Regions and College Wage Premium

	Log Change in College Wage Premium		
	Top 100	Other Univ.	No Univ.
Observed change in 1980–2015	0.291	0.211	0.168
	(0.013)	(0.009)	(0.012)
(A) No Migration			
Shut down changes in J_n	0.259	0.207	0.165
	(0.013)	(0.009)	(0.012)
(B.1) Set $\theta_c = 0.25$			
Shut down changes in J_n	0.232	0.256	0.210
	(0.013)	(0.009)	(0.012)
(B.2) Set $\theta_c = 0.75$			
Shut down changes in J_n	0.269	0.228	0.184
	(0.013)	(0.009)	(0.012)

Notes: Entries report mean changes in the logarithm of the college wage premium between 1980 and observed or counterfactual 2015. In the text, differences between observed and counterfactual log changes are expressed in percentage points. Standard errors across commuting zones are reported in parentheses. "Other Univ." denotes commuting zones with a university but no top-100 institution.

Table E.3: Task-Frontier Expansion in Top-University Regions and Structural Transformation When More Tasks Enhance Productivity

	Change in High-Skill Service Value-Added Share			Change in High-Skill Service Employment Share		
	Top 100	Other Univ.	No Univ.	Top 100	Other Univ.	No Univ.
Observed change in 1980–2015	17.11	12.85	10.52	13.91	10.66	8.67
	(0.63)	(0.34)	(0.40)	(0.58)	(0.31)	(0.37)
Shut down changes in $\mathbf{J_n}$						
— with $\phi = 0.5$	12.87	11.52	9.28	12.35	8.99	7.13
	(0.58)	(0.33)	(0.39)	(0.60)	(0.30)	(0.36)
— with $\phi = 1$	14.00	11.89	9.63	13.43	9.45	7.55
	(0.59)	(0.33)	(0.40)	(0.61)	(0.31)	(0.37)

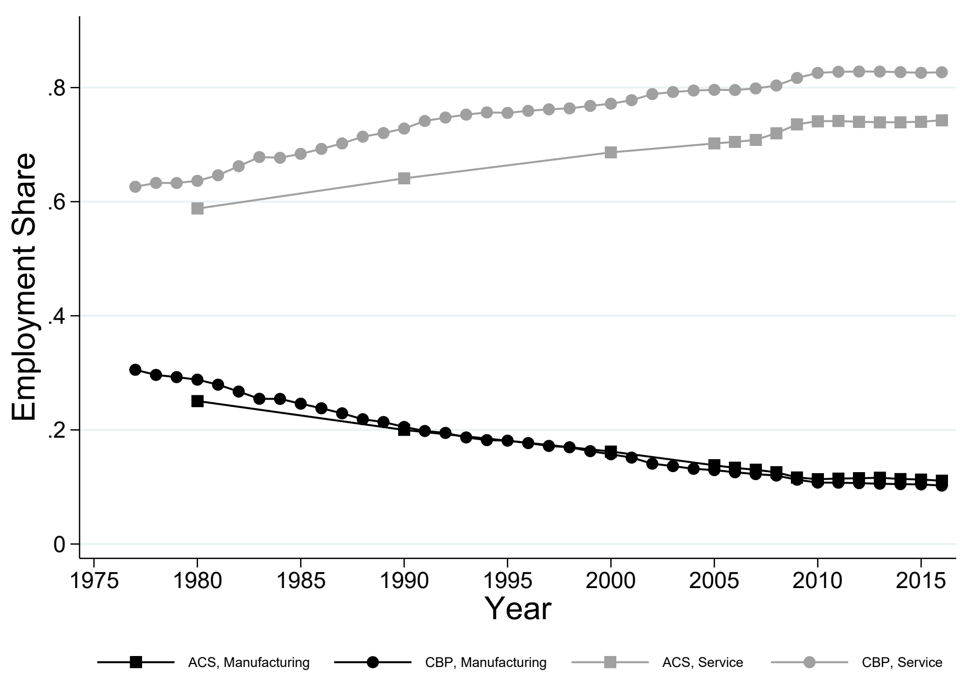
Notes: The first three rows report mean changes from 1980 to observed or counterfactual 2015, in percentage points. Standard errors across commuting zones are reported in parentheses. The contribution of each counterfactual channel is based on the difference between the observed and counterfactual changes, and the percentage explained divides this contribution by the observed change in top-university commuting zones. "Other Univ." denotes commuting zones with a university but no top-100 institution.

Table E.4: Task-Frontier Expansion in Top-University Regions and College Wage Premium When More Tasks Enhance Productivity

	Log Change in College Wage Premium		
	Top 100	Other Univ.	No Univ.
Observed change in 1980–2015	0.291	0.211	0.168
	(0.013)	(0.009)	(0.012)
Shut down changes in $\mathbf{J_n}$			
— with $\phi = 0.5$	0.252	0.236	0.192
	(0.013)	(0.009)	(0.012)
— with $\phi = 1$	0.255	0.229	0.186
	(0.013)	(0.009)	(0.012)

Notes: Entries report mean changes in the logarithm of the college wage premium between 1980 and observed or counterfactual 2015. In the text, differences between observed and counterfactual log changes are expressed in percentage points. Standard errors across commuting zones are reported in parentheses. "Other Univ." denotes commuting zones with a university but no top-100 institution.

Figure F.1: Average Employment Shares: CBP vs ACS



Notes: This figure plots the average share of employment in manufacturing and services across CZs using ACS and CBP data between 1977 and 2016.

ertheless, Figure F.1 shows that both sources capture similar long-run decline in manufacturing and increases in services.

Table F.1: High-Skill Manufacturing and Service Sectors

3-digit SIC	Description
283	Medicinal Chemicals and Botanical Products
357	Electronic Computers
376	Guided Missiles and Space Vehicles
365	Household Audio and Video Equipment
382	Laboratory Apparatus and Furniture
600-679	Finance, Insurance and Real Estate
730-738	Business Services
800-809	Health Services
810-811	Legal Services
820-829	Education Services
870-874	Engineering, Accounting, Research, Management, and Related Services

Notes: Rows 1-5 show high-skill manufacturing sectors; rows 6-11 show high-skill service sectors.

Sectoral Classification. We follow SIC classification in defining Construction (1500–1799), Manufacturing (2000–3999), and Services (4000–8812). Within manufacturing and services, we further classify industries by their college employment shares following Buera et al. (2022), using our ACS data. Table F.1 lists the industries classified as high-skill, with all remaining industries within each broad sector classified as low-skill. Despite using different data sources, our list is fairly close to that in Buera et al. (2022).

University Data. Data on universities are drawn from IPEDS managed by the National Center for Education Statistics (NCES). It gathers detailed information annually from all post-secondary institutions involved in federal student financial aid programs under Title IV of the Higher Education Act of 1965. IPEDS compiles institution-level data on various aspects of higher education in the United States, including enrollment, program completions, graduation rates, finances, and human resources. The dataset covers the years 1980 to 2022, excluding 1981 to 1983, for which data is unavailable. The main variables we use in our analysis include institution name, id, location (zipcode), sector (type of institution). Whenever a missing value occurs, we impute it with the most recent non-missing data.

US News ranking data are compiled from the official website.[F.1] Over the past two decades, this ranking is highly stable, with strong persistence over time. When aggregated into broad rank groups (e.g., top 100, top 200), the classification remains largely unchanged. Accordingly, we use the 2016 rankings throughout the analysis.

[F.1] The link is: https://www.usnews.com/best-colleges/rankings/national-universities

College Site Selection Data. We exploit the college site-selection data assembled by Andrews (2023). Each observation identifies an institution, runner-up locations, and the location ultimately selected. A siting process may contain one winner and multiple unsuccessful finalists, and a county may appear in more than one site selection. We merge towns and counties to historical county identifiers and harmonize them to the county geography used in the employment data. Relocations can also happen. For Brown University, Gustavus Adolphus College, Iowa State University, Kentucky Wesleyan College, University of Florida, and University of the Pacific, each of these colleges relocated once or several times. For example, in the case of Brown University, the Town of Warren in Bristol County was selected to be the first site of the college in 1764; however, it was decided to be relocated to Providence in 1770. In the baseline, we treat the eventual location as the winning county because it is the location exposed to the institution during the outcome period.

New-Task Data. We use job-title data from Autor et al. (2024) to measure newly emerging work. For each occupation and year, these data report the number or share of job titles classified as new. Since employment is not observed jointly by job title and commuting zone, we combine national occupation-level new-title shares with local occupational employment from the Census and ACS. Then, we use these data to compute the New Task Index, which is the employment share weighted average of occupation-level new-title shares within each commuting zone.

Population Density and Housing Rents. Population density is constructed from county population using the decennial Census and county land area using Census Gazetteer Files. For CZ-level population and land area, we sum across counties in the same CZ. All county codes and geographic area changes are properly accounted for, as we do in other part of the analysis. County-level median gross rent for 1960, 1970, 1980, 1990 and 2000 are available from the decennial Census data. Data for 2005 onward are available from ACS. We then map these data to the commuting zone level median rent, using the crosswalk between counties and commuting zones by Autor and Dorn (2013).

G Additional Empirical Results

This section provides additional empirical results, including robustness results for facts in Section 2.2. We document occupational sorting by education and broader structural transformation patterns across US CZs, show that our baseline results are robust to alternative geographic units, sector definitions and ranking lists, and compare research universities with liberal-arts colleges.

Occupational Sorting by Education. Figure G.1 compares the occupational distributions of college and non-college workers using the Nam–Powers–Boyd (NPB) score as a measure of occupational skill intensity. In both 1970 and 2010, college workers were disproportionately employed in occupations with higher NPB scores, while non-college workers were concentrated in occupations with lower scores. This pattern is consistent with the ordered comparative advantage assumed in theory: skill-intensive work is mostly performed by college workers and vice versa. However, these distributions should not be interpreted as direct measures of the task assignment in the model. The NPB score ranks *occupations* by skill intensity, whereas the model assigns workers to production *tasks* that need not correspond one-for-one to occupations. This figure instead provides supporting evidence for the broader premise that workers with different educational attainment sort systematically into work requiring different levels of skill intensity.

Structural Transformation and Its Regional Variation. Figure G.2 plots changes in employment shares between 1977 and 2016 across four sectors—manufacturing, high-skill services, low-skill services, and construction—against the log of total employment in 1977. Consistent with well-established patterns, the manufacturing sector experienced a sharp decline, high-skill services expanded significantly, and the construction sector remained largely stable. Result for low-skill services is mixed, with some regions expanding and others shrinking. Beyond these aggregate trends, the figure also reveals substantial regional heterogeneity: changes in employment shares within both manufacturing and service sectors vary markedly across CZs. Understanding this variation is a central focus of this paper.

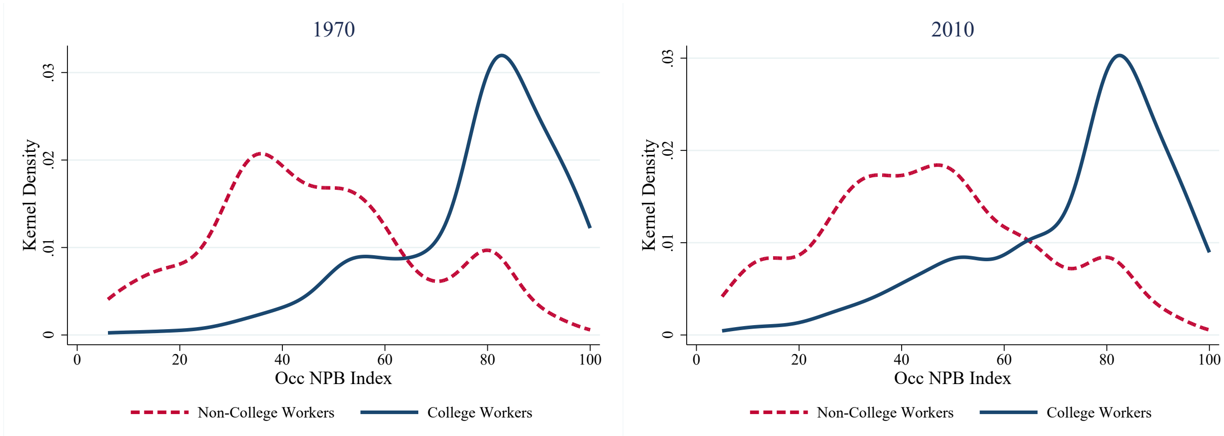
Alternative Geographic Units. Our results are not specific to commuting zones. Figure G.3 reproduces the analysis using metropolitan statistical areas (MSAs), which provide an alternative definition of local labor markets. Our baseline results hold: MSAs with universities, particularly highly ranked institutions, experienced larger increases in high-skill-service employment and larger declines in manufacturing employment.

Excluding Education Services. A potential concern of our baseline result is that universities may mechanically contribute to the measured growth of high-skill services through employment in education services, particularly in smaller college towns. To address this concern, Figure G.4 reproduces the analysis after excluding education services from the sample. The results are similar to the baseline estimates. Regions with highly ranked universities experienced larger increases in the employment share of remaining high-skill service sectors.

Alternative University Ranking. We assess the robustness of our main results using alternative ranking sources. The Academic Ranking of World Universities (ARWU) publishes annual global university rankings, with varying number of included institutions each year; the list expanded from around 500 universities during 2003-2016 to 800 in 2017 and 1,000 in 2018-2023. Consequently, the number of U.S. universities covered also fluctuates, ranging from 137 in 2016, 190 in 2017 to over 200 in 2018. As such, we use the 2018 list to classify our alternative ranking groups: top 100, top 201 and the rest. Despite the differences across different rankings, for instance, a number of universities ranked within the top 100 by U.S. News do not appear in the ARWU rankings, classifying universities based on ARWU rankings yields results that are broadly consistent with our baseline findings using the US News ranking. Replication results for Panel (b) of Figure 2 and 3 are presented in Figure G.5.

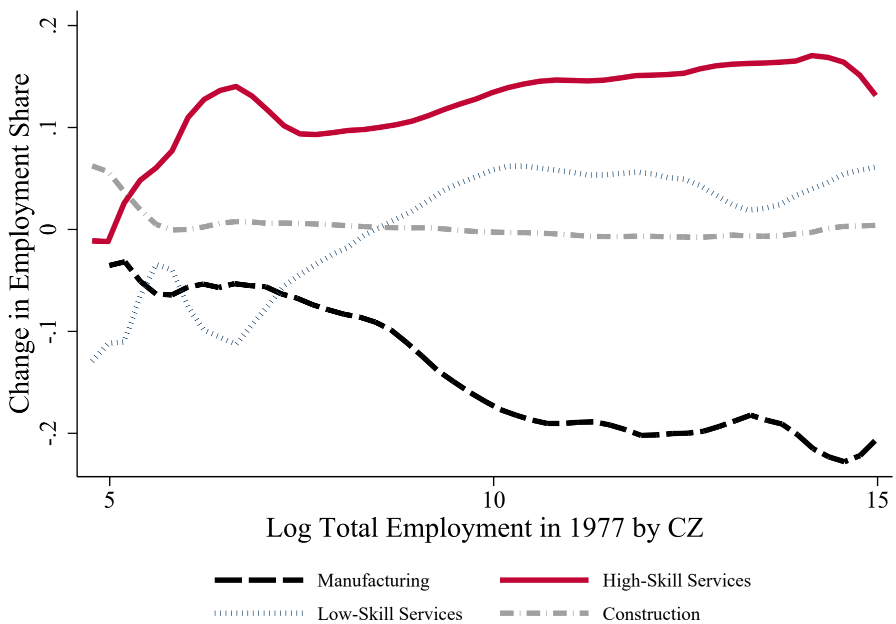
Research Universities vs. Liberal Arts Colleges. University rank may capture several characteristics, including student quality, local spending, amenities, and research activity. To distinguish among these possibilities, Figure G.6 compares regions containing research universities with those containing highly ranked liberal-arts colleges. The increase in high-skill service employment is significant for regions with research-oriented universities, whereas the difference for highly ranked liberal-arts colleges is small. Because liberal-arts colleges also attract students, employ college graduates, and contribute to local demand, this contrast suggests that the results do not reflect college presence or institutional prestige alone. Instead, the evidence is consistent with a role for university research in creating and adopting new tasks.

Figure G.1: Distribution of Occupations



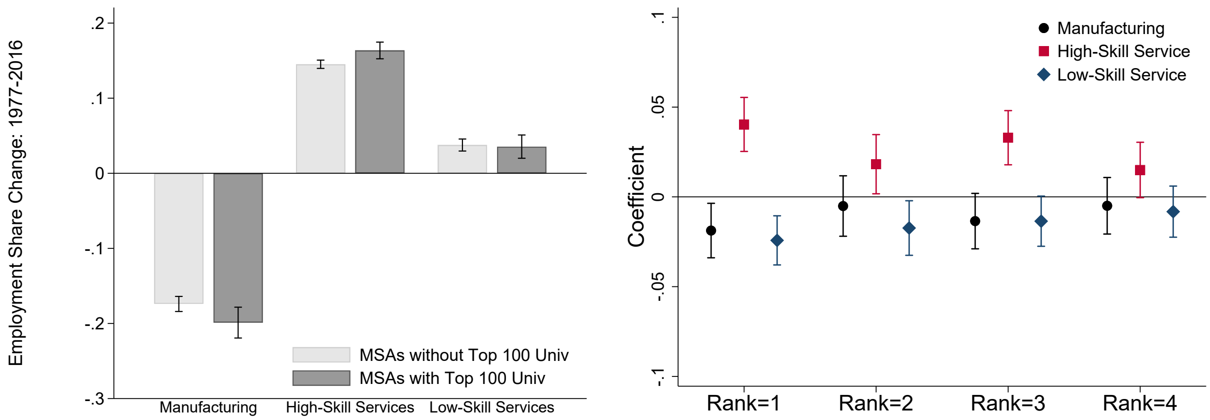
Notes: These figures plot the Gaussian kernel density of the NPB index for occupations using a bandwidth of 5, for college (navy) and non-college workers (red). Data source: ACS.

Figure G.2: Change in Employment Share by Sector and CZ: 1977-2016



Notes: This figure plots the change in share of employment in manufacturing, low-skill services, high-skill services, and construction between 1977 and 2016 (y-axis), against the log total employment in 1977 (x-axis), across CZs. The lines are generated via local mean smoothing. Data source: CBP.

Figure G.3: Universities and Local Structural Transformation: MSA-Level

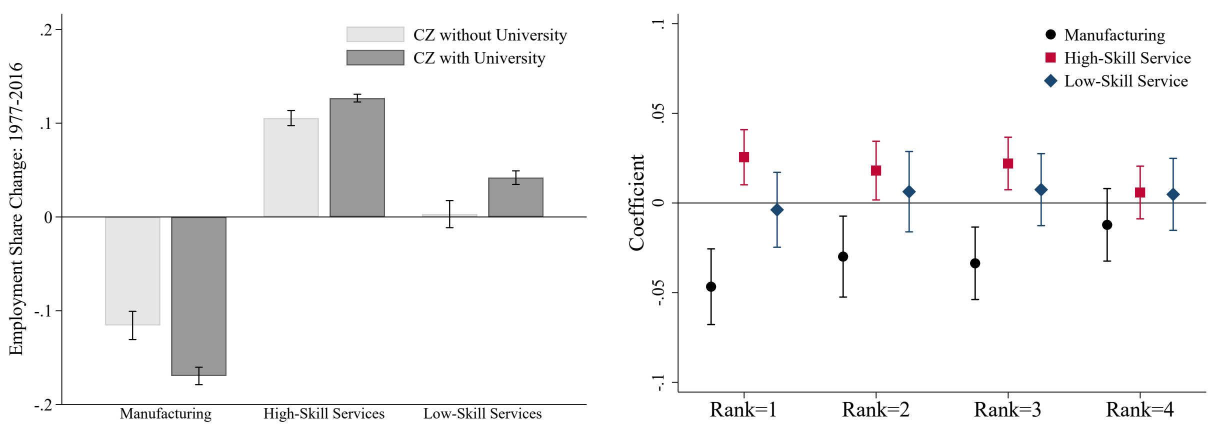


(a) Average change in sectoral employment share in MSAs with and without Top 100 universities

(b) Change in sectoral employment share in MSAs by university rankings

Notes: These figures show the average changes in sectoral employment share between 1977 and 2016 across MSA groups. In Panel (a), MSAs are grouped by the existence of a Top 100 university. Bars represent the average change of sectoral employment share in each group, and the vertical lines represent their 95 percent confidence intervals. In Panel (b), we group MSAs by the existence of a university that falls into each ranking group: "1-100 (rank=1)," "101-200 (rank=2)," "201-300 (rank=3)," "301-440 (rank=4)," and "Others." We regress changes of employment share in the manufacturing and service sectors between 1977 and 2016 on the logarithm of total MSA-level employment in 1977, the sectoral employment share in 1977, and a set of indicators on the rank group of the top university at each MSA. This figure plots the coefficients on these ranking indicators for each sector, together with their 95 percent confidence intervals. Data sources: CBP, IPEDS, and US News Best National Universities ranking.

Figure G.4: Local Structural Transformation without Education Services

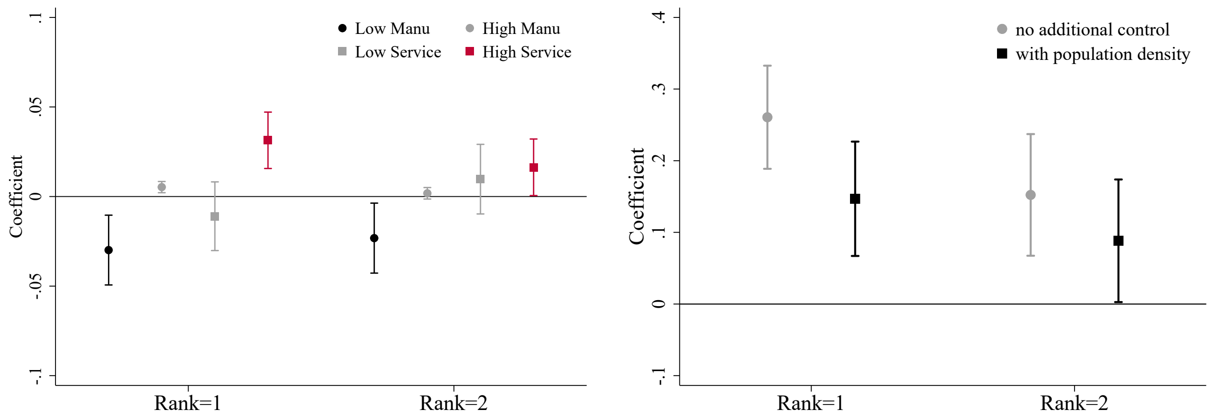


(a) Average change in sectoral employment share in CZs with and without universities

(b) Change in sectoral employment share in CZs by university rankings

Notes: These figures show the changes in sectoral employment share between 1977 and 2016 across CZ groups. "Education Services" is removed from the high-skill services; it's otherwise identical with Figure 2.

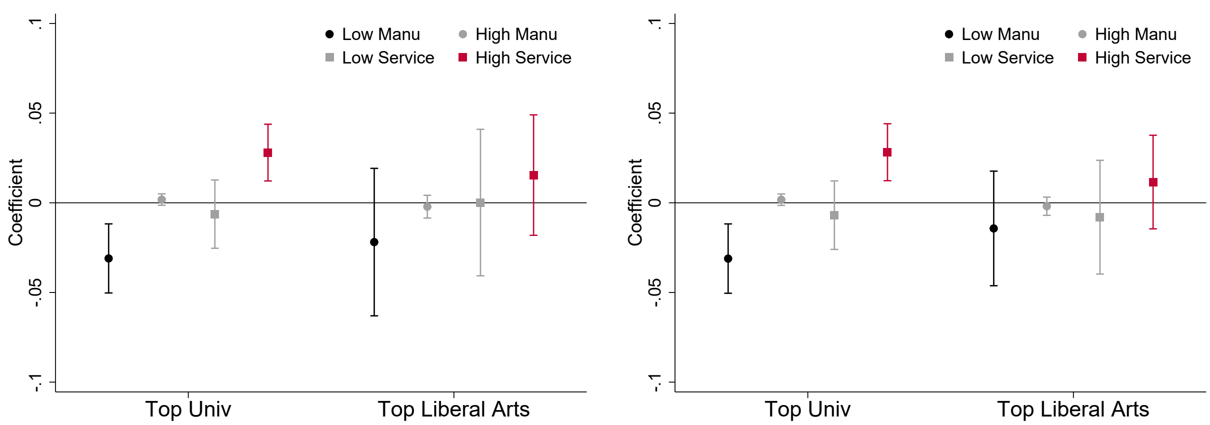
Figure G.5: ARWU Ranking



(a) Replication of Figure 2 Panel (b) **(b)** Replication of Figure 3 Panel (b)

Notes: These figures replicate Panel (b) of Figure 2 and 3, using ARWU ranking. Due to the smaller coverage of this ranking on US universities, CZs are grouped by the presence of a university that falls into: "1-100 (Rank=1)," "101-201 (Rank=2)," and "Others."

Figure G.6: Research Universities vs. Liberal Arts Colleges



(a) Top 25 Liberal Arts **(b)** Top 50 Liberal Arts

Notes: We classify CZs into three groups by the presence of a top university (top 100) or a top liberal arts college (top 25 or 50): with a top university, with a top liberal arts college only, and with neither. We regress changes of employment share in the manufacturing and service sectors between 1977 and 2016 on a set of indicators for the group indicators for each CZ, the logarithm of total CZ employment in 1977, the sectoral employment share in 1977, and CZ-level population density (log population per mi^2). This figure plots the coefficients on these group indicators by sector, together with their 95 percent confidence intervals. Data sources: CBP, IPEDS, US Gazetteer Files, as well as US News Best National Universities and Best National Liberal Arts Colleges rankings.

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