Universities and the Rise of Services*

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Abstract: Structural transformation from manufacturing to services varies significantly across regions. Using regional data from the US, we document several new stylized facts: (i) Commuting zones with universities exhibit higher growth in employment and establishment in the service sector, particularly high-skilled services; (ii) The wage premium for college-educated workers is high in commuting zones with universities; (iii) The regional variation in within-sector changes in the task contents is the primary driver of the differential growth of services; (iv) new tasks emerge predominantly in places with universities. These facts are consistent with a novel theory of local structural transformation in which universities serve as *talent* and *innovation* hubs by supplying high-skilled labor and creating new tasks by pushing the technology frontier.

Key words: structural transformation, skill premium, innovation, economic geography
JEL classification: R11, I25, L16

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1 Introduction

Structural transformation of the macroeconomy from manufacturing to services has been extensively studied, yet much less is known about its geographic variation within a country. Detroit and Pittsburgh, both historically reliant on manufacturing, have experienced divergent economic trajectories in recent decades. Detroit, once the heart of the American automotive industry, has faced significant challenges adapting to the service-oriented economy, leading to economic decline and population loss. In contrast, initially dependent on steel manufacturing, Pittsburgh successfully transformed itself into a hub for education, healthcare, and technology. A key difference between these two cities is that Pittsburgh has top universities while Detroit has none. In this paper, we study the broader variation in the rise of services across US regions and show empirically and theoretically that universities play a crucial role in shaping this spatial variation.

We begin by documenting the vastly different trends of structural transformation across US commuting zones (CZs) using County Business Patterns (CBP) data. While the Northeast and Mid-Atlantic regions—such as areas around New York City, Philadelphia, and Boston—saw significant gains in service sector employment, with some areas experiencing an increase of over 25 percentage points, the South, Mountain West, and Great Plains experienced smaller increases or even declines. Moreover, we explore the role of universities in explaining this regional heterogeneity using the Integrated Postsecondary Education Data System (IPEDS) data that includes variables such as location, enrollment, and finances for the universe of US higher education. Merging these datasets reveals two new stylized facts about structural transformation at the local level.

First, the share of service sector employment has increased significantly faster in regions with four-year colleges. Between 1977 and 2016, CZs with a college saw a 6.5 percentage point higher increase in service employment share compared to those without one, primarily driven by the high-skilled services. When we categorize regions based on the ranking of the top university in each CZ, we find that CZs with higher-ranked institutions experienced the most substantial growth in the high-skilled service sectors conditional on the initial size of employment and sectoral employment composition. To put it into perspective, CZs with a top 100 university experienced an average of 5 percentage points higher increase in high-skilled service employment share between 1977 and 2016, relative to those with universities ranked outside the top 440.

Second, the number of establishments in the service sector grew more rapidly in regions with colleges than in those without. In contrast, the number of manufacturing establishments increased until the late 1990s, then declined. This pattern suggests that the growth in service sector employment has been associated with an increase in the number of establishments, particularly in CZs with colleges.

Additionally, we establish a causal link between universities and local structural change by exploiting the natural experiment of college site selection back in the 1800s. In particular, comparing the winning and the runner-up counties in the same college-site selection experiment, which are likely very similar, we find that the former counties have shown a larger increase in service employment in the recent four decades. This evidence suggests that it is likely because of the university itself, rather than the factors that are simply correlated with the presence of a university, such as economic size, initial economic structure local amenities, etc., that shapes the geographically differential rise of services.

To illuminate the role of universities in shaping local labor market dynamics, we document two additional empirical findings based on data from the American Community Survey (ACS). Firstly, the skill/college premium on average increased more in regions with colleges than in those without. This result adds to the literature on the dynamics of the skill premium in the US (e.g., Katz and Murphy, 1992; Goldin and Katz, 2007; Acemoglu, 2003) by highlighting its regional variation. Since 1990, CZs with colleges have consistently shown a higher skill premium than those without, suggesting that local labor markets with colleges may have primarily driven the overall upward trend in the skill premium.

Furthermore, the emergence of new tasks in response to technological innovations, as documented by Autor et al. (2024), is concentrated in regions with a university. For instance, the occupation of "computer systems analysts and scientists" records many new job titles in 1990, along with the rapid growth of the IT sector and innovations in the 80s and 90s. The employment share of this occupation is significantly higher in CZs with a university than those without one. Overall, occupations with a large share of new job titles in the last decades have a large share of workers in CZs where a university exists. This suggests the role of universities in the creation of new tasks.

In an attempt to connect local labor market dynamics such as labor skills and tasks with local structural change, we leverage the rich information in the ACS data on skill, occupation, and sector in each local labor market, and decompose CZ-level change in the employment share of services into two components: changes in the skill components and the assignment of different skills to tasks, and changes in the task contents within each sector. These two channels align with the function of a university as a local talent hub that produces high-skilled labor and a local innovation hub that advances the technological frontier and encourages the development of new tasks utilized in emerging industries. Our analysis indicates that the latter role explains the majority of the geographic variation in structural transformation between 1970 and 2015, whereas changes in the skilled labor supply contribute only marginally. As an example, it captures a case in which high-skilled workers as technicians in the automotive industry in the 1970s moved to developers in high-tech services in the 2010s.

We then build a simple theory that links differential skills, tasks, and sectors, and show how universities shape the difference in local structural transformation via the two channels above. In the model, workers with different skills perform different tasks according to their comparative advantages: low-skilled workers perform low-ranked tasks, such as cleaning and machine assembly, while high-skilled ones perform high-ranked ones, such as management and R&D. As a result, the marginal cost of each task depends on the task assignment between two types of workers. Two sectors—manufacturing and services—use tasks as inputs with different input shares. In the service sector, firms adopt high-ranked tasks (e.g., management) as well as other lower-ranked tasks (e.g., maintenance, cleaning) to produce a differentiated service, which defines the endogenous task intensities within services. The equilibrium in this economy is characterized by two endogenous variables: the task assignment rule and the wage ratio between high-skilled and low-skilled workers, given their relative sizes and the set of existing tasks.

The theory predicts that regions transform from manufacturing to services at different rates when they have different patterns of innovation that add new tasks to the list of existing tasks and of the supply of high-skilled workers. This mechanism does not necessarily require changes in relative productivity or other local fundamentals such as amenities. This implication illustrates the role of universities in explaining the local structural transformation as suppliers of high-skilled workers *and* hubs for creating new tasks through innovation. For example, top universities in Silicon Valley and the Research Triangle in the US have pumped high-skilled workers with engineering and computer science degrees into the local economy and have also created new tasks and industries, such as researchers in AI, via their top-notch research. Together, these two roles have driven the local structural transformation from the traditional manufacturing sector to the high-skilled task-intensive sector, including services, without drastically changing the tasks performed by low-skilled workers.

However, these mechanisms have distinct implications for the local labor market's skill premium, echoing the race between education and technology described in Goldin and Katz (2007). While an increased supply of creators shifts tasks from traditional workers to creators, it is associated with a lower wage premium. In contrast, by generating new tasks, regions with universities stimulate higher demand for high-skilled workers, thereby increasing the equilibrium skill premium. The observation that the rising skill premium is largely driven by regions with universities suggests that the latter innovation effect may be more influential than the former talent supply effect, which is consistent with our decomposition in the quantitative results.

To quantify these mechanisms through which universities shape the local rise of services, we extend the theory to a heterogeneous-regions spatial economy that accounts for worker mobility, the local housing market, and a distinction between high and low-skilled service sectors. In particular, the mobility of high-skilled workers across regions can establish a positive feedback

loop, leading to the emergence of new tasks and the growth of the service sector: An increase in the number of tasks lowers the price index of services due to the "love of variety" effect, as more differentiated services lower the total price index. Moreover, this creation of new tasks raises the equilibrium relative wage of high-skilled workers, therefore raising their real income. As a result, the location attracts more high-skilled workers from other regions and further boosts the supply of high-skilled labor, which accelerates the shift of the economy from manufacturing to services. Lastly, we quantify this model to assess the impact of higher education on the rise of services in the US economy over the past several decades.

Our research contributes to the literature on structural transformation by focusing on its geographic variation within a country and emphasizing the role of universities. Previous works mostly focus on the macroeconomic shift from agriculture to manufacturing and then to services (Fisher 1939; Kuznets 1966; Barro and Sala-i Martin 2004; Buera and Kaboski 2012; Herrendorf, Rogerson, and Valentinyi 2014) and explore the different mechanisms underlying structural transformation in the aggregate economy, as reviewed in Buera and Kaboski (2009). These include the sectoral difference in exogenous productivity growth (Baumol 1967; Matsuyama 1992; Laitner 2000; Ngai and Pissarides 2007) and non-homothetic demand across sectors (Kongsamut, Rebelo, and Xie 2001; Matsuyama 2009; Comin, Lashkari, and Mestieri 2021). At the *sub-national* level: Caselli and Coleman II (2001) present a two-region model that jointly explains aggregate structural transformation and regional convergence; Desmet and Rossi-Hansberg (2009, 2014) develop a model of technology diffusion across space to investigate the spatial pattern of structural transformation; Eckert and Peters (2022) show the spatial variation of structural transformation can be driven by the interaction of exogenous comparative advantages across locations and the aggregate productivity growth in the agricultural sector; Takeda (2023) provides the quantifiable model on the structural transformation across geography, which is used to evaluate the impact on workers' mobility. In this paper, we examine the role of universities and provide new empirical and theoretical insights into the endogenous mechanism of the different rates of structural transformation from manufacturing to services across geography.

Our theory of labor skill and task assignment is closely related to Ricardian trade models such as Dornbusch, Fischer, and Samuelson (1977), which is applied to labor topics in Acemoglu and Autor (2011) to study how distinct skill groups perform imperfectly substitutable occupations or produce imperfectly substitutable goods. The expansion of tasks in our theory is similar to the idea of product diversity along with structural transformation (Romer 1987; Ciccone and Matsuyama 1996; Fafchamps and Helms 1996), and is consistent with recent evidence on the importance of new work (Autor et al., 2024). We develop the parsimonious model of the task-skill assignment to show how new tasks promote structural transformation and how the geographic variation of universities and the mobility of workers account for the growth of services. In this re-

spect, our theoretical framework offers a micro foundation for the "skill-biased structural change," which is often exogenously assumed in existing models in the literature (Buera et al. 2022).

Lastly, this paper contributes to the literature examining the role of universities in regional economic growth (e.g., Nimier-David 2022; Hausman 2022; Alon, Capelle, and Matsuda 2022; Babina et al. 2023; Andrews 2023), the impact of college expansion on the local labor market (e.g., Carneiro, Liu, and Salvanes 2023), and the relationship between human capital and regional development (e.g., Acemoglu and Dell 2010; Gennaioli et al. 2013). In contrast, we use our theory to guide and interpret our empirical analyses of the impact of universities on the geographic variation of structural transformation and college wage premiums. In particular we are interested in the theoretical foundation of universities in both high-skilled labor supply and innovation, from which these papers abstract.

The rest of this paper proceeds as follows. Section 2 describes the data used in our empirical and quantitative analysis. In Section 3 we present several new facts on the effect of universities on the local economy in the growth of service employment, an increase in service establishments, and the college wage premium. We additionally show the decomposition of the structural transformation to understand the source of its geographical variation. Section 4 develops a new theoretical framework of the assignment model of skills, tasks, and sectors and shows how universities contribute to local structural transformation. The theory is extended to a multi-region economy in Section 5, and we estimate the multi-region model and show quantitative results of the mechanisms underlying the relationship between universities and local structural changes. Finally, Section 6 concludes.

2 Data

In this section, we describe the datasets used in our empirical analysis and provide summary statistics on the overall structural transformation in US, the geography of local structural changes, and the spatial distribution of universities.

2.1 Data Description

Local labor market. We construct the dataset for the US local labor markets from two sources: County Business Patterns (CBP) and the American Community Survey (ACS). We sourced CBP raw data from Census for the years 1986 to 2016, and from ICPSR for the years 1977 to 1985.[1] Following the imputation methods in Acemoglu et al. (2016), we obtain annual data on county-level employment and establishment at the 1987 SIC 4-digit industry level. While CBP data have

[1]Links to CBP datasets: https://www.census.gov/programs-surveys/cbp/data/datasets.html for Census and https://www.icpsr.umich.edu/web/ICPSR/series/00022 for ICPSR.

wide coverage of firms in the local labor markets across industries, they lack detailed micro-level information on wages and the composition of workers by occupations and skills, which are useful in exploring the local economy beyond aggregate statistics. We supplement CBP data by aggregating the individual-level survey data in ACS. We restrict our analysis to individuals who were actively employed and had worked for at least 50-52 weeks in the preceding year and calculate the average annual wage and total employment by location, industry, occupation, and education level, using the individual weights included in these surveys.[2]

Occupations and skills. We source our data on local and industry-level occupations and skills from ACS for the years 1950, 1970, 1980, 1990, 2000, and every year from 2005 to 2016, which are available in IPUMS. These survey data include detailed information on individual-level education attainment, employment status, occupation, industry, and wage income. We consider two methodologies to classify occupations. First, we classify the occupations into "abstract," "routine," and "manual" using the task intensity estimates in Autor and Dorn (2013). Second, we classify the occupations by their Nam-Powers-Boyd scores[3], which measure the skill intensity of each occupation. "Skill" is defined as the educational attainment at the individual level: for example, a college graduate carries more skills and human capital than a high school graduate. To focus our analysis on the role of universities, we create a binary skill variable where '1' corresponds to individuals who have completed a four-year college or higher degree and '0' otherwise. We aggregate individual data by county or commuting zone (CZ) for each occupation category and skill and obtain a series on total local employment and average local wage by occupation and skill.

Information on universities. We construct our main dataset on US universities from the Integrated Postsecondary Education Data System (IPEDS), which spans from 1980 to 2022, except for the years 1981 to 1983, and covers the universe of US higher-education institutions. Individual year's data files are merged into a single data frame by the unique identification of each institution. This dataset contains detailed information on the location, type, enrollment, and graduation of each institution, as well as financial information, including grants and expenses. Given our focus on the role of universities in creating high-skilled labor and new tasks, we broadly classify these institutions into four-year colleges and the rest. We measure the quality of the university by defining groups based on their rankings. The ranking data was retrieved from the 2016 Best Na-

[2]In the Appendix, Table B.1 demonstrates that ACS data on local labor markets are comparable to CBP data, even though the ACS employment data are derived from individual surveys. Figure B.1 further illustrates the similarity between these two data sources in capturing overall trends in structural transformation. This comparability enables us to use the detailed information provided by the ACS for a more in-depth analysis of structural transformation changes by skill and occupation.

[3]The Nam-Powers-Boyd scores are available at http://www.npb-ses.info/.

tional Universities Ranking in the US News website.[4] In total, the list contains approximately 440 institutions, which are categorized as "rank=1 (1-100)", "rank=2 (101-200)", "rank=3 (201-300)", "rank=4 (301-443)", and "others."

Merged dataset. To build a consistent regional dataset that can be compared across time and regions, we convert the raw data into a unified classification system for location, industry, and occupation, following the crosswalk files used in Autor and Dorn (2013); Autor, Dorn, and Hanson (2019).[5] For local labor market geography, we convert Census State Economic Areas, Census County Groups, Census, and ACS Public Use Micro Areas to 1990 Commuting Zones (CZs). For industry classification, we conduct a weighted crosswalk into a consistent SIC 1987 4-digit industry code system. For occupations, we convert all Census occupation codes *occ* to the *occ1990dd* code used in Autor and Dorn (2013). In sum, our merged regional dataset includes the following variables in each CZ: industry, occupation, skill, employment, wage, number of establishments, a "college" dummy variable indicating the existence of a four-year college, and a "rank" variable indicating the ranking group of the best university in the region.

2.2 Data Summary

We provide descriptive statistics of employment shares in different sectors across our two sources, as well as the spatial distribution of colleges by their ranking groups.

Overall structural transformation. Table B.1 in the Appendix provides summary statistics of employment from the CBP and ACS for selected years across CZs in the US. Employment shares in the manufacturing sector exhibit a notable decline from 1980 to 2016 across both CBP and ACS data sources, decreasing from an average of approximately 0.29 to about 0.10. Additionally, CZs without a college consistently display higher manufacturing employment shares compared to those with one, reflecting the potential impact of higher education on local labor market compositions. In contrast, the service sector employment share experienced a substantial increase from 1980 to 2016, rising from an average of approximately 0.59–0.64 to approximately 0.74–0.83. Furthermore, CZs with a college tend to have greater service sector employment shares compared to those without. These trends not only underscore the broader structural shift from manufacturing to services within the US economy over the past few decades—which has been studied extensively in the literature—but also highlight the potential impact of higher education

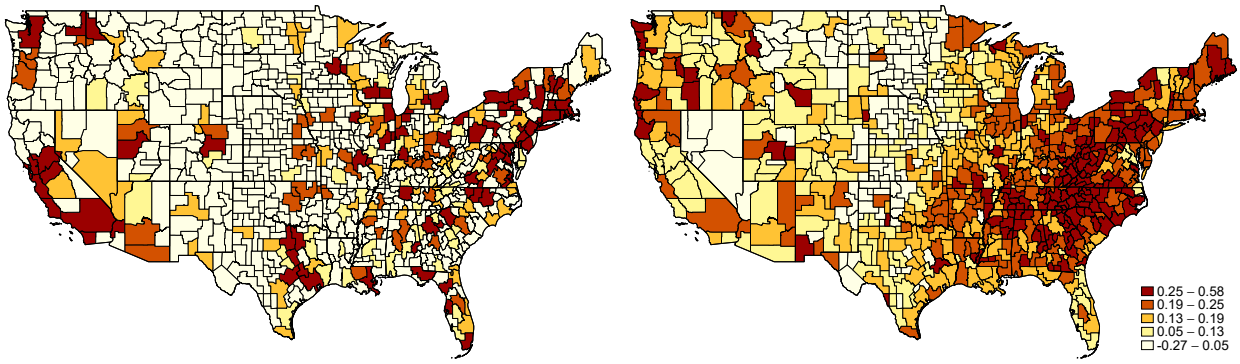
[4]The link to the website is: https://www.usnews.com/best-colleges/rankings/national-universities. The ranking data are not available in earlier years, and we use the recent rankings as a proxy for earlier years. This is because, even though individual rankings may fluctuate over time, the rank group in which each university is classified remains relatively consistent.

[5]This crosswalk is available on David Dorn's website https://www.ddorn.net/data.htm.

on shaping the geographic variation in structural transformation patterns, on which our paper focuses.

Geography of universities in the US. Figure 1 (a) visualizes the geographic distribution of US colleges by rankings across CZs in 2016, based on data from the US News Best National Universities Ranking. The map uses a gradient from dark to light to represent different rank groups, with darker areas indicating CZs that host higher-ranked universities (rank 1) and lighter areas representing zones with lower-ranked universities or none (rank 5). This visualization reveals substantial geographic disparities in the quality of higher education institutions across the US, with clusters of higher-ranked universities primarily located in the Northeastern and Western regions, while the Midwest and Southern regions also show a notable presence of top-ranked schools.

Figure 1: Geography of US Colleges and Change in Service Employment Share

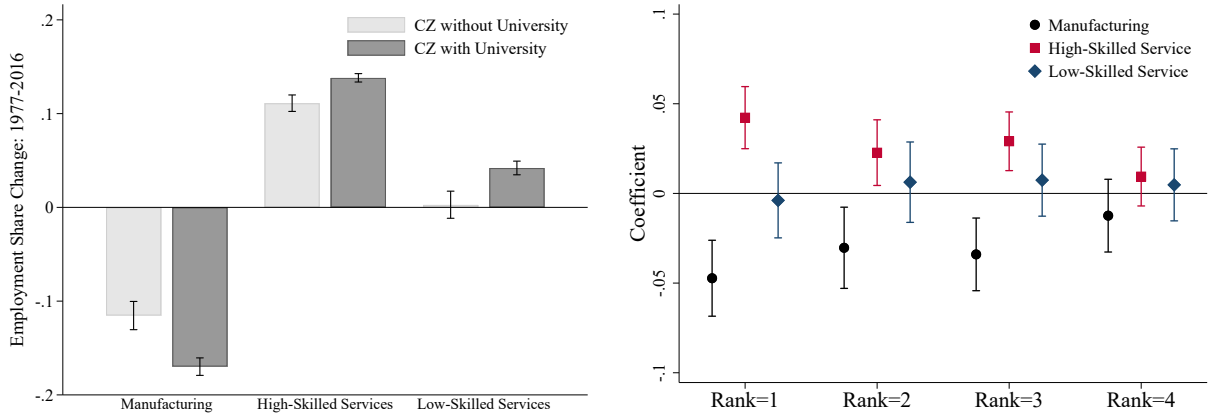


(a) US Colleges by Rankings **(b)** Change in Employment Share of Services

Note: Panel (a) shows the distribution of colleges by 2016 rankings. Commuting zones in the US are divided into five groups: from dark to light, rank=1; rank=2; rank=3; rank=4; and others. The data source is the 2016 US News Best National Universities Ranking. Panel (b) illustrates the change between 1977 and 2016 in the share of employment in the services sector across commuting zones in the US that are divided into five quintiles. The data source is CBP.

Geography of structural transformation. Figure 1(b) illustrates the distribution of changes in the employment share in the service sector across CZs in the United States between 1977 and 2016. The main message from this figure is the significant variation in the rise of the service sector across regions. While the Northeast and Mid-Atlantic regions, including areas around New York City, Philadelphia, and Boston, saw significant gains in service sector employment, with some areas experiencing an increase of over 25 percentage points, the South, Mountain West, and Great Plains experienced smaller increases or even declined. Our primary hypothesis is that the presence of colleges plays a crucial role in shaping this regional variation in structural transformation, which we explore further in the following section.

Figure 2: Local Structural Transformation



(a) With and Without Universities **(b)** By University Rankings

Note: These figures show the average changes in sectoral employment share between 1977 and 2016 across CZs by region groups. In Panel (a), CZs are grouped by the existence of a four-year 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 CZs 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 employment in CZ in 1977, the sectoral employment share in 1977, and a set of indicators on the rank group of the top university in each CZ. 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.

3 Motivation: Universities and the Local Economy

We begin by presenting four new facts on local structural transformation and labor markets, demonstrating the role universities play in shaping their spatial variation in Subsection 3.1. Next, we exploit the geographic variation of the college site selection from 1839 to 1954 to identify the impact of universities on the rise of services in Subsection 3.2. Lastly, we break down the changes in the service employment share into different components to highlight the key drivers of local structural transformation in Subsection 3.3.

3.1 Stylized Facts

Fact 1: Structural transformation is more pronounced in CZs with colleges, particularly in those with a top-tier institution.

We present descriptive evidence on the variations in structural transformation among CZs. First, we compare two different groups of CZs based on the presence or absence of a four-year college (university) in the CZ. Panel (a) in Figure 2 shows the average change in sectoral employment share for these two groups. From 1977 to 2016, the average increase in service sector employment share was 17.8 percentage points in CZs with a university, compared to 11.3 in CZs without one.

This cross-region difference holds for both high-skilled and low-skilled sectors. However, high-skilled sectors saw much bigger growth in their employment shares, while that of the low-skilled ones is close to 0, especially in regions without a university. On the flip side, employment share in the manufacturing sector experienced a substantial decline, more so in CZs with a university.

Not all universities are alike. Next, we investigate the role of a "good" university. Moreover, regions differ in other factors that may influence local structural transformation. For example, Panel (b) of Figure 1 illustrates that the structural transformation from manufacturing to services can be biased toward large cities. Furthermore, various sectoral shocks in recent decades, such as the import competition, could be associated with the initial sectoral composition of CZs. To account for these factors, we regress the changes in employment shares in the manufacturing and service sectors on indicators of university rank within CZs, controlling for the total employment size and sectoral employment share in the initial year of 1977.

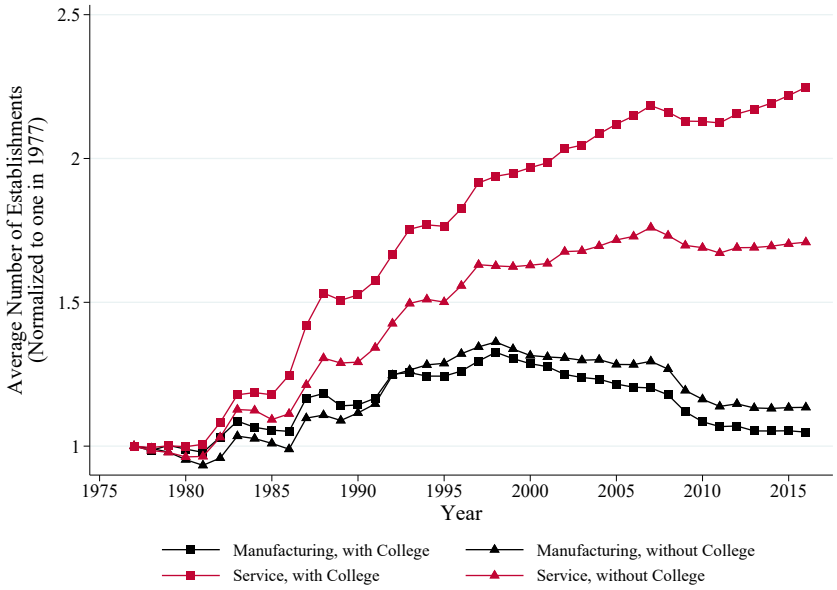
Panel (b) of Figure 2 plots the coefficients on university ranking categories, which are interpreted as the impact of being in each rank group relative to the lowest one (i.e., "Others"). The coefficients for CZs with a higher-ranked university, particularly those with a Top 300 university, are statistically significant for manufacturing and high-skilled service sectors, while for low-skilled service sectors, the differences across groups are minimal. This result suggests that in CZs with a high-ranked university, the rate of structural transformation from manufacturing to services is more pronounced, even when accounting for initial employment size and sectoral composition. When it comes to different service sectors, it is the high-skilled services that drive the difference across CZs with different ranks of universities.

Fact 2: The number of establishments in the service sector grew more quickly in CZs with colleges than in those without; and the number of establishments in the manufacturing sector increased until the late 1990s, then declined.

In Figure 3 we illustrate the cumulative growth in the average number of establishments in the manufacturing and service sectors across CZs with and without a four-year college from 1977 to 2016. The data is normalized in 1977, allowing for a comparison of growth rates over time relative to that base year. The figure highlights the distinct trends in the development of these sectors, with a significant divergence between CZs with a college presence and those without, particularly in the service sector.

The service sector experienced substantial growth in both types of CZs, with a more significant increase in regions that have a college presence. By 2016, the average number of service sector establishments in CZs with colleges had more than doubled, indicating robust expansion compared to those without colleges, which also saw growth but at a slower rate. This trend suggests that the presence of higher education institutions is positively correlated with the pro-

Figure 3: Average Number of Establishments by Location and Sector



Note: This figure plots the changes in average number of establishments by sector across CZs with or without college between 1977 and 2016, with 1977 data normalized to one. The red (black) points and lines show the average number of establishments in the service (manufacturing) sector. Within a sector, squares (triangles) are the average number of establishments in that sector for CZs with (without) a four-year university. The data source is CBP.

liferation of service sector establishments, potentially due to the higher concentration of skilled labor and innovation-driven industries associated with college towns.

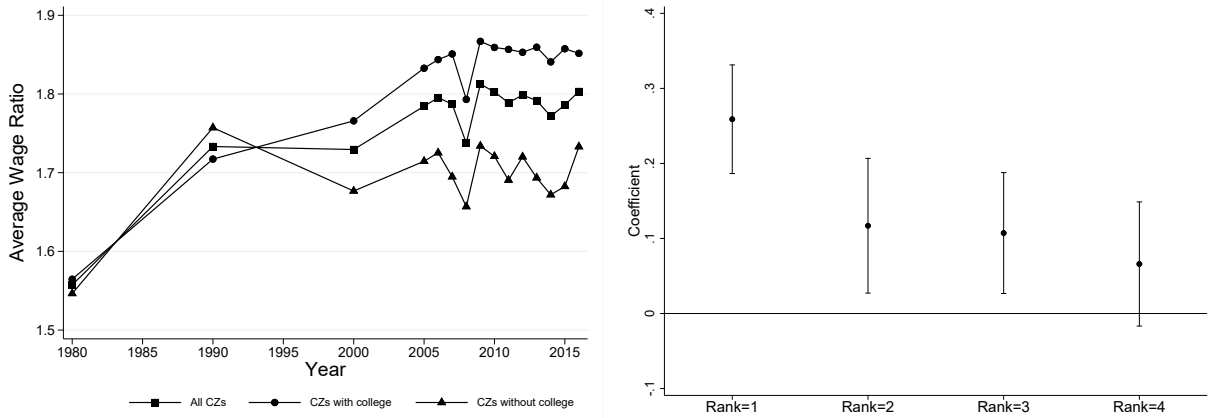
In contrast, the manufacturing sector shows a different pattern. The number of manufacturing establishments remained relatively stable, fluctuating slightly but generally returning to near their 1977 levels by 2016. Meanwhile, both groups of CZs experienced a decline in manufacturing establishments since the late 1990s, reflecting broader structural shifts in the economy away from manufacturing and toward services, with a slightly stronger decline in CZs with colleges. These patterns again underscore the importance of educational institutions in shaping local economic structures and the differential patterns in the rise of services across regions.

Fact 3: On average, the skill premium increased more in CZs with colleges relative to those without.

Panel (a) in Figure 4 shows the average skill premium, or college wage premium, across CZs with and without a four-year college, from 1980 to 2016. The line with squares, representing the overall average across all CZs, indicates a general increase in the skill premium between 1980 and 2005, consistent with existing studies (e.g., Goldin and Katz, 2007). After a significant decline and reversal during the Great Recession, it remained relatively stable, with only minor fluctuations.

We go beyond this well-studied overall trend by separating CZs based on the presence or

Figure 4: Skill Premium Changes by Location



(a) Skill Premium in CZs with and without University

(b) Relative Skill Premium in CZs with Universities at Different Rank Groups

Note: Panel (a) plots the skill premium (college wage premium), averaged across all CZs, CZs with college and without, between 1980 and 2016. Panel (b) plots the estimates of the coefficients and their 95 percent confidence intervals for the regression of the CZ-level changes in skill premium between 1980 and 2016 on a set of indicators on the rank group of the top university in each CZ, based on US News. The data source is ACS.

absence of a college. For CZs with a college, there is a clear and consistent general upward trend in the skill premium over the entire period: From 1980 to the early 2000s, the skill premium in these regions steadily increased, faster than the national average. While its growth trend stopped after the recession, the skill premium maintained its position well above the levels observed in the 1980s and 1990s, as well as those in other regions. In contrast, CZs without a college display a rather different pattern. While the skill premium in these regions initially rose similarly to, or even faster than, that in CZs with a college, it began to decline around 1990 with occasional minor increases. Since 2000, it has been consistently lower than that in CZs with colleges. Over time, the divergence between these lines indicates an increasing gap in the skill premium between regions with and without a college. It also suggests that local labor markets with colleges may have primarily driven the widely documented upward trend in skill premiums in the literature.

Similar to the analysis above, we investigate the skill premium across regions with universities under different ranking groups. Panel (b) presents that the skill premium changes between 1980 and 2016 are significantly higher in regions with the top 300 universities than the rest, with the top 100 ones seeing the highest rise. This result bears semblance to the result of local structural change.

Fact 4: New tasks emerge predominantly in regions with a university.

Autor et al. (2024) document that new work emerges in response to technological innovations.

We expand their analysis by focusing on the geographical distribution of new occupation titles. Their data shows the number of new titles by occupation and year. However, employment at the occupation title level or the direct information on the geography of these new titles is unobserved. Therefore, we take an indirect approach. Using Autor et al. (2024)'s dataset on new titles, we calculate a "new title share" for each occupation and year. These shares provide some useful information on which occupations saw the biggest increases in job titles in a given year. The question of interest is: where are the occupations with many new titles located?

Using the occupation-level employment data from ACS, we estimate the difference in employment shares by occupation and year between CZs with universities and those without. The result for the top 20 occupations ranked by the "new title share" is shown in Figure 5 for the years 1980, 1990, and 2000. The majority of these occupations show significantly positive differences in employment shares—those with most new titles have a stronger presence in regions with a university. For example, the top-ranked occupation in 1990 was "computer systems analysts and scientists," likely due to the rapid IT sector growth in the 80s and 90s. The employment share in this occupation is significantly higher in CZs with a university than those without one, suggesting that the majority of the newly emerged job titles in this occupation were located in regions with universities. This observation motivates our modeling of universities being innovation hubs that create new tasks.

3.2 Identifying the Impact of Universities

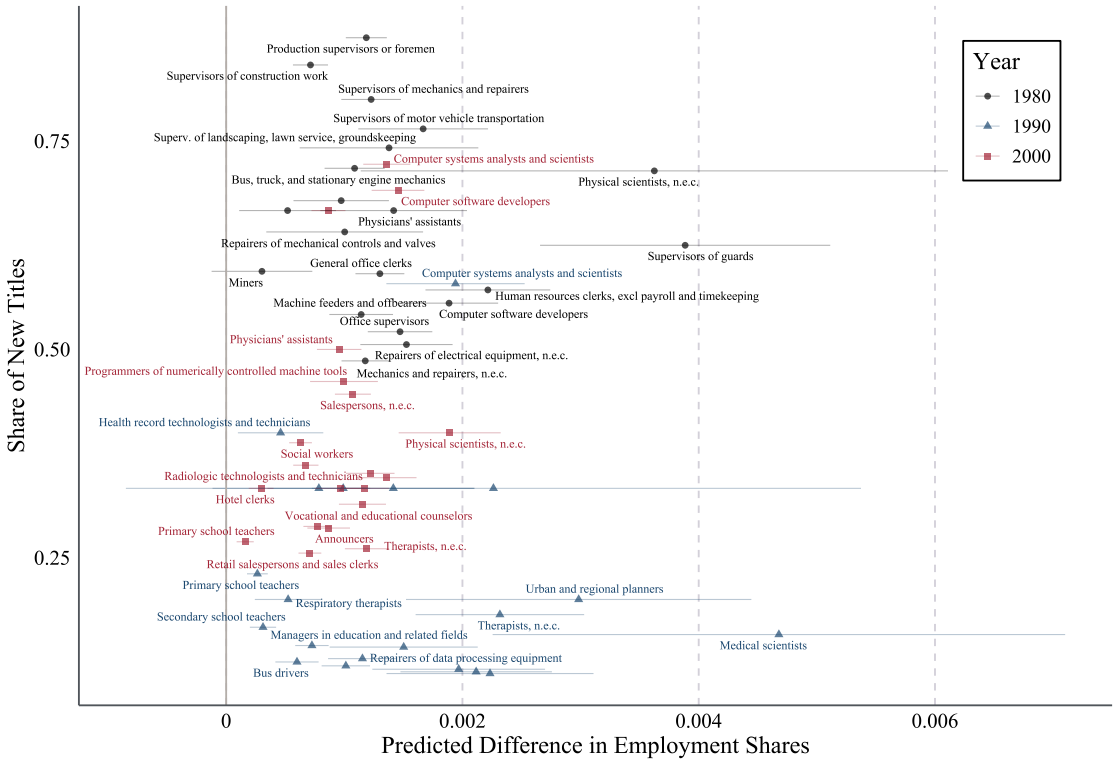
One may be concerned that the location of a university is endogenous, therefore the observed differential structural changes can be driven by factors that are not directly related to the role of a university, such as economic size, initial economic structure, and other location specifics that can be correlated with the presence of universities. To identify the causal impact of having a university on local structural shifts, we follow the strategy by Andrews (2023) and Russell, Yu, and Andrews (2024) which compare the winning county with the runners-up in the same college site-selection experiment that occurred between 1839 and 1954.[6]

Figure 6 plots the dynamics of the logarithm of service sector employment for the winner and runner-up counties. This indicates that the winning counties show a large increase in service employment on average. To better identify the impact of universities on the rise of services, we next estimate the following equation:

$$\Delta \ell_c^j = \beta^j \text{Treatment}_c + \gamma_1^j \ell_{c,1977}^j + \gamma_2^j \log L_{c,1977} + \gamma_e^j + \epsilon_c^j, \tag{1}$$

[6] In generating our benchmark results, we drop colleges that have relocated after the college site selection experiment. A robustness test that includes them using their new locations gives similar results. Details on the data can be found in Appendix C.2.

Figure 5: Employment Share in "New Tasks" Across CZs



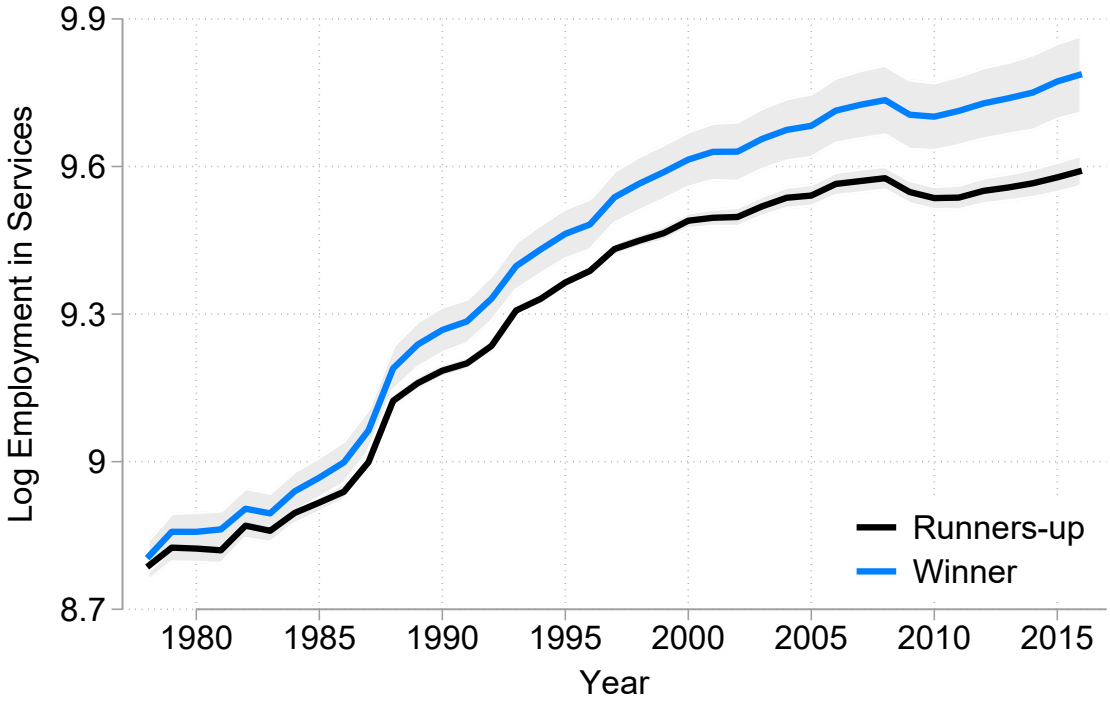
Note: The vertical axis shows the share of new titles by occupation in the years 1980, 1990, and 2000, using the "New Work" data constructed by Autor et al. (2024). The horizontal axis shows the coefficient estimates for the cross-CZ regression of employment share by occupation on a university dummy. Data source: ACS.

where j represents the sectors (manufacturing or services). The dependent variable $\Delta\ell_c^j$ is the change in employment share for sector j in county c from 1977 to 2016: $\Delta\ell_c^j = \ell_{c,2016}^j - \ell_{c,1977}^j$. Since there is no relocation of colleges in the period, Treatment$_c$ is invariant for a specific county, taking a value of 1 if county c was the winner of a college site selection and 0 if it was a runner-up in the same site selection experiment. The initial sectoral employment share ($\ell_{c,1977}^j$) and the initial log total employment ($\log L_{c,1977}$) control for sectoral composition and economic size at the start of our analysis period, considering the potential differential growth trajectories between winning and runner-up counties over the decades. They help ensure that the estimated long-run effect of winning a college site on employment share changes is not biased by pre-existing differences. γ_e stands for the experiment fixed effects so that comparisons are between winning and runner-up counties for the same college. This sidesteps a handful of cases where a county that had been rejected by one college later on was chosen for another university. For example, Maricopa County won the selection for Arizona State University but lost to the University of Arizona.

The identification assumption of our empirical analysis is that the winning and runner-up

counties are similar along observed and unobserved dimensions; some of these selections were even randomly assigned. Table 1 presents the coefficient estimates together with the robust standard errors. Considering the correlation of economic activities within a region, we report standard errors clustered at the CZ level. Our main parameter of interest of interest, β^j, is estimated to be negative for the manufacturing sector and positive for the service sector. This result is consistent with our descriptive evidence: Relative to runner-up counties, manufacturing employment share in winner counties declined more, whereas the service sector's employment share increased more. We also notice that initial conditions matter for the differential structural change patterns across counties.

Figure 6: Service Employment: Winner versus Runner-up Counties



Note: The blue (black) line shows the logarithm of average employment in services from 1977 to 2016 for the winner (runner-up) counties in the college site selection. The gray-shaded area is the 95 percent confidence interval. The Data source is ACS.

3.3 Decomposing the Employment Shift to Services

We explore the different sources that could contribute to the geographic variation of structural transformation using our local labor market data on skill and occupation in a simple accounting framework. Consider the following decomposition of the employment share of sector j in location i:

$$\ell_{ij|i,t} \equiv \frac{L_{ij,t}}{L_{i,t}} = \sum_{s \in Skill} \sum_{o \in Occ.} \frac{L_{ijso,t}}{L_{it}} = \sum_{s \in Skill} \sum_{o \in Occ.} \ell_{is|i,t} \cdot \ell_{iso|is,t} \cdot \ell_{ijso|iso,t} \tag{2}$$

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

	Manufacturing	Service
Winning Site	-0.009**	0.012**
	(0.046)	(0.013)
Sectoral employment share in 1977	-0.618***	-0.629***
	(0.000)	(0.000)
Log total employment in 1977	-0.013***	0.018***
	(0.000)	(0.000)
Constant	0.149***	0.377***
	(0.000)	(0.000)
Observations	930	932

Note: This table reports the coefficient estimates of equation (1). The robust standard errors clustered by commuting zones are in parentheses. ***, ** and * indicates significance at the 1, 5 and 10 percent level, respectively.

where $\ell_{is|i,t} \equiv L_{is,t}/L_{i,t}$ is the share of workers of skill s in location i; $\ell_{iso|is,t} \equiv L_{iso,t}/L_{is,t}$ is the share of workers of skill-task (s, o) among workers of skill s in location i; and $\ell_{ijso|iso,t} \equiv L_{ijso,t}/L_{iso,t}$ is the share of workers in industry-skill-task (j, s, o) among labor with skill-task (s, o) at location i.

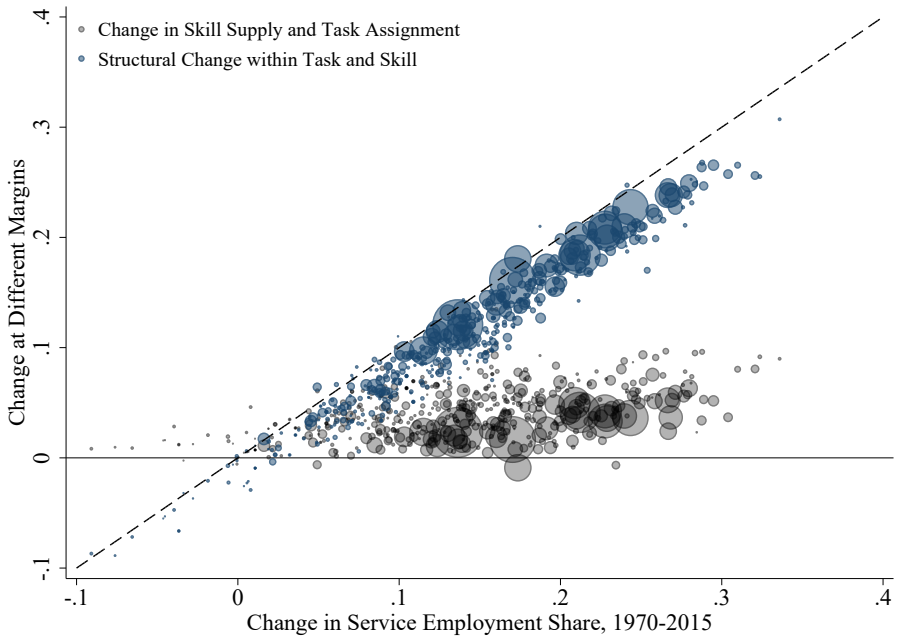
The local employment share changes between $t-1$ and t can be broken down into three parts in equation (2). The change in the first component, $\ell_{is|i,t}$, represents changes in the supply of workers with different skill levels in the local labor market. In our context, the possession of a college degree is used to define different skills. For the second component in equation (2), $\ell_{iso|is,t}$, its change captures the assignment of workers with specific skills to different tasks, which can vary over time even within a sector. Intuitively, workers without a college degree who were assigned to machine assembly jobs in the automotive industry during the 1970s might have been reassigned to maintenance jobs in the same industry in the 2000s. These two parts are aligned with skill-biased structural transformation and task upgrading or downgrading because of technological progress. We let $\ell_{iso|i,t} \equiv \ell_{is|i,t} \cdot \ell_{iso|is,t}$ refer these two components together and define the following:

$$\Delta\ell^{\mathbb{A}}_{ij|i,t} = \sum_{s\in Skill}\sum_{o\in Occ.} \mathcal{W}^{\mathbb{A}}_{ijso,t-1} \cdot \Delta\ell_{iso|i,t}, \tag{3}$$

where the weights $\mathcal{W}^{\mathbb{A}}_{ijso,t-1}$ are defined at the initial period $t-1$ associated with the change in $\ell_{iso|i,t}$ between period $t-1$ and t.

Instead, the change in the third component on the right-hand side of equation (2), $\ell_{ijso|iso,t}$, is the reallocation of workers within the same skill level and same task to a different sector. For example, a high-skilled researcher in the automotive industry might transition to a research role in the high-tech service sector as manufacturing declines and service rises. Put differently,

Figure 7: Decomposition of Employment Share Changes in Services: 1970-2015



Note: This figure shows the decomposition of structural transformation at 480 commuting zones (CZ). The horizontal axis represents the change in service employment share between 1970 and 2015; the vertical axis represents each of the two components described in equations (3) and (4). The black circles represent changes (3), and the blue circles are changes (4). The size of each circle corresponds to the total employment in the CZ in 1970. The dashed line shows the 45-degree line. The data source is ACS.

this component also illustrates changes in task content and skill requirements across sectors over time. To evaluate the importance of this component in the structural transformation, we compute the following:

$$\Delta \ell^{\mathbb{B}}_{ij|i,t} = \sum_{s \in Skill} \sum_{o \in Occ.} \mathcal{W}^{\mathbb{B}}_{ijso,t-1} \cdot \Delta \ell_{ijso|iso,t} \tag{4}$$

for location i and sector j. The weights $\mathcal{W}^{\mathbb{B}}_{ijso,t-1}$ equals to the initial employment share $\ell_{iso|i,t-1}$ in period $t-1$.

We now show how the geographic variation of these changes given by equations (3) and (4) represents the geographic variation of the rate of structural transformation from manufacturing to services. Figure 7 plots them for the service sector (j) across CZs (i) between 1970 ($t-1$) and 2016 (t) in the vertical axis, versus the change in employment share in services on the horizontal axis, based on the ACS. The size of each circle corresponds to the total employment in each CZ in 1970. Two key observations are as follows: First, changes in task assignments for workers with a given skill level and the supply of skills show relatively little variation across CZs, as indicated by the black circles that demonstrate small locational differences. second, the reallocation of workers across sectors within the same skill and task, accounts for most of the regional dif-

ferences. This suggests that the reallocation of tasks across sectors, including the emergence of new tasks concentrated in the service sector, plays a significant role in explaining the geography of structural transformation.

The two primary channels identified in our decomposition in equation (2)—the variation in the supply of skilled and unskilled workers, and changes in task and skill contents across sectors—align with the two major roles of a university in the local economy. As talent hubs, universities contribute to the local labor market by producing high-skilled workers. This increased supply of skilled labor over time reduces the cost of human capital for local firms, thereby facilitating sectoral expansion. As innovation hubs, universities push the technological frontier and foster the creation of new tasks and industries. Collaboration with local firms, startups, and government entities accelerates the diffusion of knowledge and facilitates the commercialization of new technologies, fostering the emergence of new sectors and the reallocation of labor across industries. We formalize these two roles in the following theory section, where we elaborate on how universities contribute to the rise of services.

4 A Simple Theory of Local Structural Transformation

We present a simple theoretical framework to provide new insights into (i) the relationship between skills, tasks, and sectors in the local economy and (ii) how higher education and research can accelerate structural transformation through changes in task content across sectors. Subsection 4.1 lays out the model environment, and Subsection 4.2 defines the competitive equilibrium. Subsection 4.3 provides comparative statics for the key variables in the model. Subsection 4.4 explains how a simple model provides new insights into the structural transformation, which are connected to the empirical findings in Subsection 4.5.

4.1 Setup

We consider a single economy embedded in a large economy. There are two types of agents indexed by ℓ, where $\ell = n$ refers to *workers* without a college degree and $\ell = c$ stands for *creators* who have received higher education. The total mass of each type in this economy is given by L^n and L^c. There are two types of products labeled as manufacturing goods and services. The manufacturing goods are homogeneous and freely tradable in a large economy, while services are differentiated and nontradable.

Preference. All agents inelastically supply one unit of efficient labor. The labor market is competitive, and wages are given by w^n and w^c for each type of worker. Preference of individuals of

type ℓ is given by:

$$\ln U^{\ell} = \alpha\mu \ln X^{\ell} + \alpha(1-\mu)\ln m^{\ell} + (1-\alpha)\ln h^{\ell}, \quad \alpha,\ \mu \in (0,1) \tag{5}$$

where X^{ℓ} is consumption aggregator of services, m^{ℓ} is consumption of the manufacturing goods and h^{ℓ} denotes the consumption of housing. $1-\alpha$ is the expenditure share on housing and $\alpha\mu$ is that on services. Individuals consume differentiated services within a bundle. We assume the consumption aggregator of services is a constant elasticity of substitution (CES) across differentiated services available in the economy. The expenditure share on a differentiated service j is given by: $x(j) = \big(p(j)/P\big)^{1-\eta}$, where $\eta > 1$, $p(j)$ is price of a service j and P is an ideal price index of services.

Tasks done by individuals. Continuous tasks are indexed by $\sigma \in [0, K]$, where the set of tasks existing in this economy is characterized by K. The index K captures the *frontier* of the tasks that increase as new tasks are introduced in the economy. Without loss of generality, we suppose that $K > 1$. Tasks are horizontally differentiated, for example, car assembly, weaving textiles, constructing housing, and AI research.

Production of tasks only requires efficient labor. One unit of efficient labor provided by type ℓ worker produces $z^{\ell}(\sigma)$ units of task σ. Creators can perform any task, therefore, $z^{c}(\sigma) > 0$ for all existing tasks $\sigma \in [0, K]$. Workers can perform a subset of the tasks, and there exists $\overline{\sigma} < K$ such that $z^{n}(\sigma) \geq 0$ for tasks $\sigma \in [0, \overline{\sigma}]$ and $z^{n}(\sigma) = 0$ for tasks $\sigma \in [\overline{\sigma}, K]$. Intuitively, $\overline{\sigma}$ is the exogenous upper limit of the task that workers can perform without higher education. While workers cannot perform tasks close to the frontier, such as scientific research, an increase in $\overline{\sigma}$ implies that workers can perform more tasks. Tasks are ordered such that the relative productivity of workers to creators is decreasing as task index σ increases: $\mathcal{Z}(\sigma) = z^{n}(\sigma)/z^{c}(\sigma)$ with $\mathcal{Z}'(\sigma) < 0$ and $\mathcal{Z}(0) < \infty$.

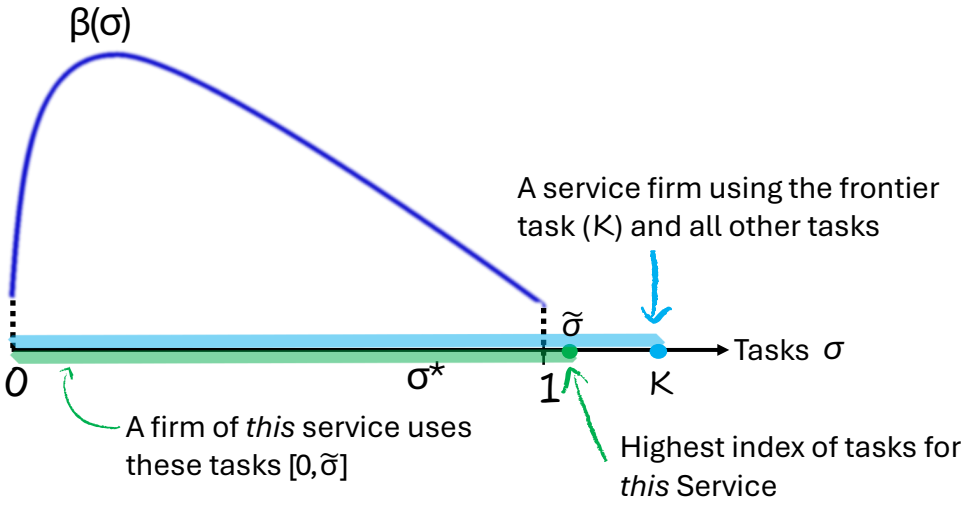
Tasks are not traded, and the market for tasks is perfectly competitive. Unit production cost of task σ by worker type ℓ is: $\delta^{\ell}(\sigma) = w^{\ell}/z^{\ell}(\sigma)$. In a local labor market, task σ is performed by workers instead of creators if:

$$\omega \leq z^{n}(\sigma)/z^{c}(\sigma), \tag{6}$$

where the left-hand side is the relative wage of workers to creators: $\omega = w^{n}/w^{c}$. Given the wage ratio between workers and creators, we let σ^{*} refer to the index of task where condition (6) holds with equality. Therefore, workers sort into tasks over $[0, \sigma^{*}]$ and creators over $[\sigma^{*}, K]$. The price of task σ is given by $\delta(\sigma) \equiv \min\{\delta^{c}(\sigma),\ \delta^{n}(\sigma)\}$.

Manufacturing firms. A representative firm producing goods combines tasks in the interval $[0, 1]$. The production technology is Cobb-Douglas, and to produce one unit of manufacturing

Figure 8: Tasks in Production of Manufacturing and Services



goods, a firm's expenditure on specific task σ in $[0,1]$ is given by $\beta(\sigma) \in (0,1)$. $\beta(\sigma)$ is continuous. The fixed interval of tasks $[0,1]$ in the production of homogeneous goods is intuitive for traditional goods, which require a fixed set of tasks that always exist. For future reference, we also define the cumulative expenditure share as follows:

$$\overline{\beta}(\sigma) = \int_0^{\sigma} \beta(\sigma')d\sigma' \tag{7}$$

Goods are freely traded across locations, and therefore, we normalize their price.

Service firms. Services are differentiated. There are competitive firms for each service, and their production technology exhibits constant return to scale.[7] Specifically, each service firm is characterized by its highest index of tasks, which must be greater than 1. Consider a firm with the highest index of tasks, $\sigma \in [1,K]$. The technology of production is given by Leontief technology using a continuum of tasks $\sigma' \in [0,\sigma]$. Intuitively, the production of a service exploiting the highest index of tasks σ requires *all* tasks below σ: management in the service sector requires simple tasks (e.g., cleaning, driving) that are also utilized in the manufacturing sector.[8] Given the marginal cost of each task $\delta(\sigma)$, the cost of producing one unit of service characterized by its highest task σ is given by

$$\gamma(\sigma) = \int_0^{\sigma} \delta(s)ds, \tag{8}$$

[7]In the baseline model, we consider perfect competition of firms for each differentiated service, and therefore we can consider a representative firm for each service. Services are differentiated by their core task, and therefore, the number of services in the economy equals $K-1$. The results are qualitatively similar when we extend this framework with monopolistic competition without free entry, which leads to a positive surplus which we suppose land owners and government extract.

[8]The advantage of Leontief technology is that the marginal cost of supplying each service is linear in the marginal cost of each task.

and the expenditure share of the service firm on different task $s \in [0, \sigma]$ in production is:

$$A(s,\sigma) = \frac{\delta(s)}{\int_0^{\sigma} \delta(\sigma')d\sigma'} = \delta(s)/\gamma(\sigma) \tag{9}$$

Since each differentiated service corresponds to an index of its highest task in production $\sigma \in [1, K]$, we refer to $\epsilon(\sigma)$ as the expenditure share on each service. Figure 8 presents the visualization of the setup.

4.2 Equilibrium

The market clearing condition for workers states the sum of the expenditure of firms producing manufacturing goods and services on tasks produced by workers equals the aggregate income of workers. This is analogous for creators. Combining them, we derive the labor market clearing condition in terms of the relative wages of workers to creators:

$$\omega = \frac{\alpha(1-\mu)\overline{\beta}(\sigma^*) + \alpha\mu \int_1^K x(\sigma') \left[\int_0^{\sigma^*} A(s,\sigma')ds\right] d\sigma'}{\alpha(1-\mu)\left[1-\overline{\beta}(\sigma^*)\right] + \alpha\mu \int_1^K x(\sigma') \left[\int_{\sigma^*}^K A(s,\sigma')ds\right] d\sigma'} \frac{L^c}{L^n} \equiv \Gamma\left(\sigma^*, \frac{L^c}{L^n}, K\right), \tag{10}$$

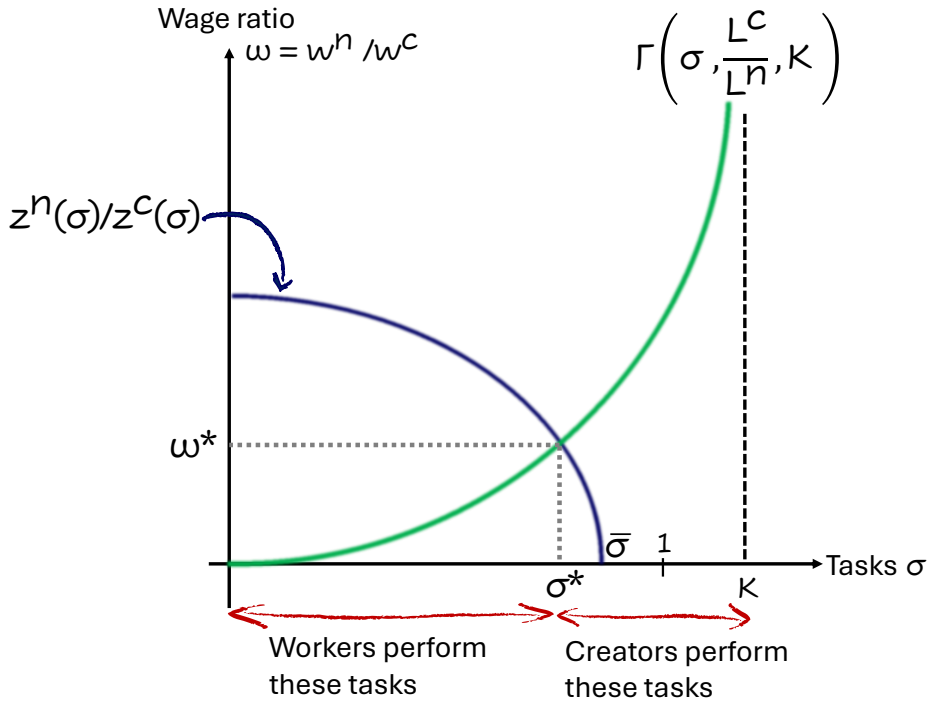
where, in the numerator, individuals spend a fraction $\alpha\mu$ of their income on services; expenditure share of individuals on a service differentiated by task $\sigma \in [1, K]$ is $x(\sigma)$; and the input share of tasks $s \in [0, \sigma^*]$ produced by workers in the production of the service is $A(s, \sigma)$. We now formally define the equilibrium for this single economy.

Definition 1. *Consider a single economy. Given the mass of workers L^n and creators L^c, the equilibrium is characterized by the wage ratio of workers to creators ω^* and task assignment σ^* that solves condition (6) with equality, and labor market cleaning condition (10).*

Figure 9 illustrates the competitive equilibrium. We can see $\Gamma(\sigma, L^c/L^n, K)$ is increasing in σ and $\lim_{\sigma\to\infty} \Gamma(\sigma, L^c/L^n, K) = \infty$. Since the right-hand side of the relative labor productivity of workers to creators in condition (6) is decreasing in σ, the threshold of task index σ^* and wage ratio ω^* are uniquely determined in equilibrium.

Proposition 1. *Given the mass of workers L^n and creators L^c, we have a unique equilibrium (σ^*, ω^*) in this economy. Tasks indexed by $[0, \sigma^*]$ are performed by workers; and those indexed by $[\sigma^*, K]$ are performed by creators. Thus, in equilibrium core tasks for services are always performed by creators.*

Figure 9: Equilibrium



4.3 Race between Education, Dissemination and Innovation

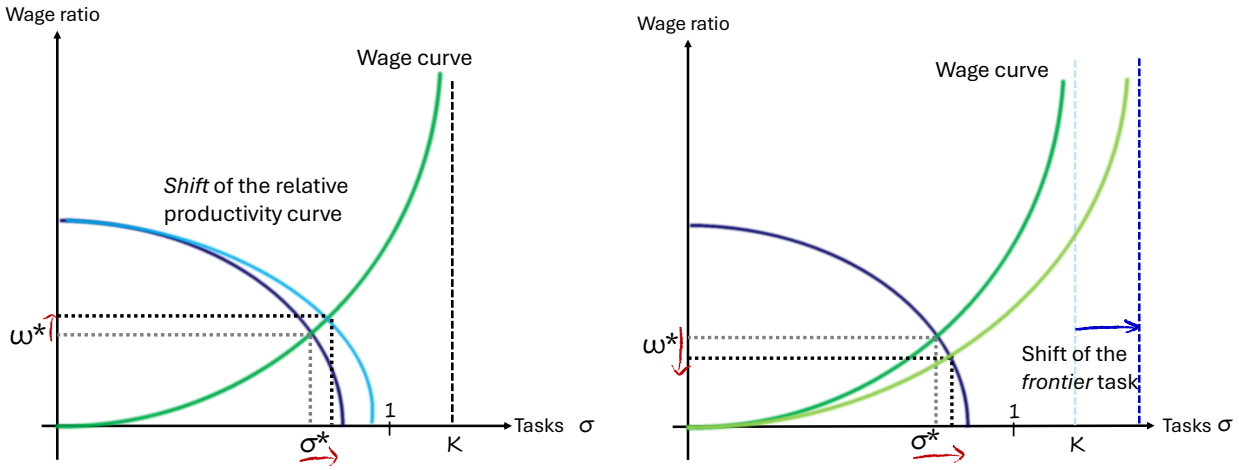
Now, we consider the effects of education, task dissemination, and task innovation on the local labor market through the lens of our model. In this model, education increases the number of creators relative to workers, therefore larger L^c/L^n. Given a fixed number of tasks K and an individual's expenditure share, the supply of creators results in a higher relative wage between workers and creators because of an upward shift of the wage curve: $\Gamma(\sigma, \kappa L^c/L^n, K) > \Gamma(\sigma, L^c/L^n, K)$ for any $\kappa > 1$ and σ. This results in a smaller threshold of task σ^*. Therefore, we have *downgrading* of tasks for creators.[9]

Next, we study the impact of two types of changes in tasks. First, we study the impact on the local labor market if workers can adopt new technology that expands the set of tasks available to them, captured by a large value of $\overline{\sigma}$. The rightward shift of $\overline{\sigma}$ implies that workers become able to perform new tasks for which creators have relatively high productivity. This *dissemination* process results in an increase in the relative productivity of workers performing tasks of a higher index. This leads to a higher relative wage ω^* and an expansion of the set of tasks $[0, \sigma^*]$ that workers perform in equilibrium. The intuition is the following: when workers can

[9]Another aspect of education is the improvement of the productivity of creators relative to workers for the tasks that they do. In the model, this is captured by the upward shift of the curve of relative productivity $\mathcal{Z}(\sigma)$ for $\sigma \geq \sigma^*$. However, this does not change the equilibrium wage ratio ω^* and threshold of task σ^*. As a result, we do not take into account the impact of education on local structural transformation.

perform more tasks with the dissemination of technology, workers indeed perform more complicated tasks captured by higher σ, and demand for workers increases given the wage curve. The left panel of Figure 10 presents the visualization of this.

Figure 10: Dissemination and Innovation of Tasks



(a) Dissemination **(b)** Innovation

Second, we explore the impact of introducing new tasks on the local labor market. The model captures the emergence of new tasks by shifting the frontier of K. While this does not alter the relative productivity of workers, it does cause a shift in the wage curve. We can show that when there are new tasks Δ such that frontier changes $K \to K + \Delta$, the wage curve $\Gamma(\sigma, L^c/L^n, K)$ becomes flatter for the incumbent tasks $\sigma \in [0, K]$. Intuitively, newly-created tasks must be performed by creators and become core for the new services. This disproportionately increases the demand for relatively complex tasks on the denominator of equation (10), and the equilibrium wage ratio ω^* becomes low. In addition, the set of tasks performed by workers $[0, \sigma^*]$ expands because creators are more specialized in complicated tasks. The right-hand side panel of Figure 10 shows this effect. The following proposition summarizes these effects:

Proposition 2. *Given the mass of workers L^n and creators L^c, (i) the wage ratio ω^* increases and set of workers' tasks $[0, \sigma^*]$ shrinks if a relative number of creators L^c/L^n increases; (ii) the wage ratio ω^* increases and the set of workers' tasks $[0, \sigma^*]$ expands if dissemination of technology for workers is accompanied by an increase in $\overline{\sigma}$; and (iii) the wage ratio ω^* decreases and the set of workers' tasks $[0, \sigma^*]$ expands if there is innovation creating new tasks that expand the set of all tasks from $[0, K]$ to $[0, K + \Delta]$.*

Formal proof of this is provided in Appendix A.1. Together, the race between education, task dissemination, and task innovation may have an ambiguous impact on the wage ratio and the set

of tasks performed by workers and creators. Yet, each of the three channels indicates a distinct response from the local labor market.

4.4 The Rise of Services

We now use the model to illustrate how and why services grow in the local economy. The various mechanisms that contribute to an increase in the share of employment in services are summarized in the following proposition:

Proposition 3. *An increase in the share of employment in the service sector is associated with (i) an increase in the average real income of individuals; (ii) lower unit costs for services based on the incumbent core tasks; (iii) an increase in the relative price of frontier service to the wage of creators; (iv) a higher share of the value of tasks produced by workers in the price of frontier service; and (v) a higher relative wage of creators to workers.*

In our model, the mass of labor inputs in the service sector, denoted by E_{Service}, equals the mass of workers and creators producing tasks used for the service sector. Combining the assignment of tasks (6), profit maximization of service firms (8) and the labor market clearing conditions (10), we can express the change in service labor share:

$$d\log\frac{E_{\text{Service}}}{L^n+L^c} = d\log\frac{\bar{w}}{P} + d\log\int_1^K\left(\frac{\gamma(\sigma)}{P}\right)^{1-\eta}d\sigma + d\log\frac{\gamma(K)}{w^c} + d\log\left[1+\frac{1}{\gamma(K)}\left(\int_0^{\sigma^*}\frac{w^n}{z^n(\sigma)}d\sigma\right)\left(\frac{w^c}{w^n}-1\right)\right], \tag{11}$$

where $\bar{w}$ is the average income of individuals and $\gamma(K)$ is the price of the service based on the frontier task K. Each term corresponds to the statement in the Proposition 3. We explain the intuition as follows while relegating a formal proof to the appendix.

On the right-hand side of equation (11), the first and second terms capture the demand channel. In particular, an increase in the real income from the change in the price index for services (P) leads to higher demand for services and lower prices of tasks intensively used in the production of services ($\gamma(\sigma)/P$), requiring further input of labor in the service sector.

The next two terms on the right-hand side capture the race between innovation and education that determines the relative price of service and the pattern of input of tasks. Intuitively, with a substantial increase in the set of tasks as a result of innovation, an increase in the price of new services may outweigh an increase in the wage of creators. This, in turn, increases the number of individuals who perform tasks in these new services. In the last term, $\frac{1}{\gamma(K)}\left(\int_0^{\sigma^*} w^n/z^n(\sigma)d\sigma\right)$ is the share of the value of tasks produced by workers in the price of frontier service. Given wages,

the change in the task assignment from creators to workers leads to an increase in this share, and therefore, task upgrading for workers is associated with an increase in service employment share. Finally, an increase in the wage premium of creators (w^c/w^n) is associated with an increase in service employment share due to higher demand for creators which leads to a rise in services.

4.5 The Role of University: Linking Theory with Stylized Facts

Based on Proposition 2 and Proposition 3, we derive the theoretical implications for the impact of the existence of higher education on the rate of structural transformation at the local level and relate them to the facts documented in Section 3.

First, higher education is associated with a supply of high-skilled individuals with college degrees. Following Proposition 2 (i), this leads to a higher wage ratio ω^*, which turns out to be a lower wage premium for creators. Nevertheless, the wage premium of college graduates to non-graduates has increased over time, and the premium is higher in the commuting zones with institutes of higher education, as evidenced by Fact 3 in Section 3. Therefore, this effect may not be dominant in equilibrium. In addition, an increase in the supply of creators results in the reallocation of tasks from workers to creators, which is captured by a decrease in σ^*. Then, in the last term of the right-hand side of equation (11), a reduction in wage premium (w^c/w^n) and reallocation of tasks from workers to creators is associated with a lower share of labor inputs in services *ceteris paribus*. Overall, Fact 1 in Section 3 could not be consistent with this.

Second, universities are the hub of technological progress in the local economy. In Proposition 2 (ii) and (iii), we emphasize the dissemination and invention of tasks through technological progress. Together, these factors shift the allocation of tasks from creators to workers. When low-skilled individuals adopt new technology to perform relatively complex tasks, and high-skilled individuals need to perform new tasks developed with innovation, they reallocate tasks previously performed by high-skilled (creators) to low-skilled (workers). This task reallocation increases the share of value added of workers in the existing services and lowers unit costs for services based on the incumbent core tasks. These effects predict an increase in the share of labor inputs in the service sector, as in Proposition 3 (ii) and (iv).

Third, the relative magnitude of task dissemination and invention determines the direction of the wage premium change. If innovation is so strong that it creates enough new tasks, the wage premium for creators will increase. In our model, an increase in new tasks captured by the rightward shift of their frontier (K) corresponds to an increase in the number of services produced by different firms. As we have seen in Section 3, the increase in employment in the service sector is predominantly driven by the growing number of establishments. Therefore, we may see this as evidence for a large expansion of new tasks intensively used in services. In turn, the model

predicts higher real income because of a lower price index and a higher rate of labor reallocation from the manufacturing sector to the service sector, as we present in Proposition 3 (i) and (v). In particular, high-ranked universities in the local economy can foster structural transformation through this channel, consistent with the differential rates of structural transformation across different groups of universities shown in Figure 2.

We also note that one potential mechanism that diminishes or magnifies the race between these channels is the mobility of high-skilled individuals relative to the low-skilled. Specifically, in the US, university graduates are more mobile across locations within a country, and the direct effect of their supply on the local labor market is not necessarily large. Furthermore, high-skilled individuals tend to gravitate towards locations that offer a wider range of services. To understand this channel, we extend the simple model to a multi-region economy in the next section.

5 Quantitative Implications

In this section, we extend the model in the previous section to quantify the role of universities and decompose the local growth of services. We proceed in three steps. First, we present the quantifiable version of our theory for an economy with multiple regions and three sectors: manufacturing, low-skilled services, and high-skilled services. In the model, we endogenize the creation of new tasks such that regions with universities can add new tasks with lower costs. Furthermore, we introduce local housing markets with differential housing prices, which leads tothe mobility of creators across regions.[10] Second, we define the general equilibrium and derive an equilibrium relationship for the growth of services and wage premiums for creators. The equations can be used to isolate the different channels in the theory in explaining the variation of service growth and wage premiums across locations. Finally, we use the US data to quantify the role of universities in the local economy.

5.1 Setup of the Quantitative Model

There are N locations. Each location is indexed by subscripts $i = 1, 2, \cdots, N$, which corresponds to each CZ in our empirical analysis. There are three sectors indexed by $k \in \{M, S, H\}$: manufacturing (M), Low-skilled local services (S) and High-skilled services (H). Manufacturing goods are freely traded across locations. The mass of creators in a country is exogenous and given by: $\overline{L}^c = \sum_{i=1}^{N} L_i^c$. As in the simple model, there are two types of individuals: workers (n) and creators (c). Individuals supply one unit of labor to engage in a task, as described in Section 4.1.

[10] Since highly educated individuals are more mobile than low-educated workers in the data, we assume that creators have free mobility across regions.

The condition (6) holds for wage ratio $\omega_i \equiv w_i^n / w_i^c$ for all locations and the cost of each task in location i is given by $\delta_i(\sigma)$.

Technology of Manufacturing and Low-Skilled Service Firms. We continue to assume Cobb-Douglas production technology for manufacturing firms. They use the fixed set of tasks $T^M = [0, \tau^M]$ and the cost share of each task is given by $\beta^M(\sigma) \in (0,1)$. We note that $\overline{\sigma}^M$ is exogenous and the same across all locations. We suppose a similar production technology for low-skilled local services to the manufacturing sector. Specifically, the production technology of firms in the low-skilled services is Cobb-Douglas using the set of tasks $T^S = [0, \tau^S]$, and we let $\beta^S(\sigma)$ refer to the input share of each task in production. Therefore, the demand for tasks in location i for manufacturing and low-skilled service sectors are given by:

$$\begin{aligned} \delta_i(\sigma) q_i^M(\sigma) &= \beta^M(\sigma) Y_i^M, \quad \sigma \in T^M \\ \delta_i(\sigma) q_i^S(\sigma) &= \beta^S(\sigma) Y_i^S, \quad \sigma \in T^S \end{aligned} \tag{12}$$

where $q_i^k(\sigma)$ is units of task σ used for sector k; and Y_i^k is total value of production of sector k. Low-skilled services are non-tradable, and the price of low-skilled services is given by:

$$P_{Si} = \exp\left[\int_0^{\tau^S} \beta^S(\sigma) \ln \delta_i(\sigma) d\sigma\right] \tag{13}$$

Technology of High-Skilled Service Firms. Turning to the high-skilled services, we consider the generalized version of the production technology described in Section 4. A high-skilled service based on task σ as the highest index of the tasks of input combines all tasks below it. For the discrete number of tasks, (8) and (9) can be expressed as follows:

$$\gamma_i(\sigma) = \left[\int_0^{\sigma} \delta_i(s)^{\rho} ds\right]^{1/\rho}, \quad A_i(s,\sigma) = \frac{\delta_i(s)^{\rho}}{\int_0^{\sigma} \delta_i(s')^{\rho} ds'}, \tag{14}$$

where ρ controls substitutability between tasks in production of high-skilled services.[11]

Preference. We introduce three sectors in consumption. We assume the CES combination of low-skilled local services and high-skilled services in consumption, and the indirect utility of individuals of type ℓ in location i becomes:

$$\mathbb{W}_i^{\ell} = \frac{w_i^{\ell}}{P_i^{\alpha\mu} Q_i^{1-\alpha}}, \tag{15}$$

where $1-\alpha$ is expenditure share on housing, $\alpha\mu$ is expenditure share on services, and P_i is price index for services:

$$P_i = \left[\left(P_{Si}/\varkappa_S\right)^{1-\epsilon} + \left(P_{Hi}/\varkappa_H\right)^{1-\epsilon}\right]^{1/(1-\epsilon)} \tag{16}$$

[11] The specification in Section 4 is the special case when $\rho = -\infty$.

$(\varkappa_S, \varkappa_H)$ controls the relative weight of each sector in consumer utility and ϵ is the constant elasticity of substitution between two service sectors. For high-skilled services, the lower tier of utility from the consumption of differentiated services is the same as in the simple theory. Therefore, expenditure minimization implies the following shares of service j in consumer expenditure:

$$x_{Hi}(j) = \left[\frac{p_{Hi}(j)}{P_{Hi}}\right]^{1-\eta} \frac{\left(P_{Hi}/\varkappa_H\right)^{1-\epsilon}}{P_i^{1-\epsilon}} \tag{17}$$

New Tasks. We introduce *investors* to endogenize the set of available tasks in each location. In the absence of investment, the frontier of the tasks in location i is defined as $K_i = 1$. The number of potential investors in the economy determines the number of tasks to add through investment beyond the index $K_i = 1$. In the economy, one unit of investment can generate $\phi(\sigma)$ units of new tasks for those with an index of $\sigma > 1$.[12] We assume that the return on investment decreases in the complexity of tasks: $\phi'(\sigma) < 0$. Intuitively, complex tasks with higher indices are difficult to create. Investment in each task requires one unit of land and fixed costs, which depend on a positive constant cost f and the existence of a university, θ_i. When a university is present in the location, θ_i is strictly positive, and it is zero otherwise. The level of universities is represented by the value of θ_i. Therefore, the fixed cost of adding new tasks is lower when the location has a university, and a large value of θ_i implies a lower cost with a highly ranked university. We let λ_i refer to the value of return on investment for each task in location i. Then, the creation of new tasks in each location v_i can be expressed by:

$$v_i = g(\underset{-}{f}, \underset{+}{\theta_i}, \underset{+}{\lambda_i}), \tag{18}$$

where g is a continuous function. Consequently, the frontier task in location i is given by $K_i = 1 + v_i$. A location with a higher-ranking university (larger θ_i) exhibits a higher index for the frontier task, and a higher return on investment (λ_i) leads to a higher index for the frontier task. Lastly, the bid for one unit of land (π_i) is determined by the zero profit condition for investors. Detailed microfoundation is in Appendix A.2.

Housing and Land. Each location has a competitive developer who provides housing. Developers produce housing using homogeneous goods and land for housing development. Given the price of housing (Q_i), developers choose the input of homogeneous goods to maximize their profit. Therefore, the housing supply in location i is:

$$H_i = \Lambda_i Q_i^{\varrho}, \tag{19}$$

[12] We assume that the investment, including fixed costs, takes the form of homogeneous goods traded in international markets throughout this paper.

where Λ_i absorbs local characteristics, and ϱ represents housing supply elasticity. Developers bid for land for construction, and in turn, the bid rent for developed land (r_i) extracts profit from developers. In equilibrium, we suppose $\pi_i = r_i$. Therefore developers' bid land rent for housing equalizes the bid land rent for innovation by investors. Detailed microfoundation is in Appendix A.3.

Mobility. Creators ($\ell = c$) are freely mobile across locations, while workers ($\ell = n$) are not able to move. Given the preference (5), the free mobility of creators implies that their indirect utility is equalized across locations:

$$\mathbb{W}_i^c = \frac{w_i^c}{P_i^{\alpha\mu} Q_i^{1-\alpha}} = \overline{u}, \quad \forall\, i \tag{20}$$

where $\overline{u}$ is given in the economy.[13] Intuitively, housing prices rise in tandem with wage growth and the influx of creators to a location such as San Francisco, acting as a dispersion force in the economy.

5.2 General Equilibrium

We now define the equilibrium for this multi-region economy.

Definition 2. *We suppose that creators can change their locations. Given (i) the set of parameters in preference and technology* $\{\alpha, \mu, \rho, \epsilon, \varkappa_S, \varkappa_H, \beta^M(\sigma), \beta^S(\sigma), \eta, \varsigma\}$*, (ii) the set of functions related to universities and new tasks* $G(f, \theta_i)$ *and* $\phi(v)$*, (ii) the productivity difference between creators and workers in the aggregate economy* $\mathcal{Z}(\sigma)$*, and (iii) the heterogeneity across locations in the mass of workers* (L_i^n)*, universities* (θ_i)*, land endowment* $(\mathcal{O}_i)$*, productivity of developers* (Λ_i) *and mass of creators in the country* $(\overline{L}^c)$*, the equilibrium is characterized by the following endogenous variables: wage of workers and creators* (w_i^n, w_i^c)*, the mass of creators* (L_i^c)*, the task assignment* (σ_i^*)*, the frontier of tasks* (K_i^*)*, housing prices* (Q_i) *and common real income* $(\overline{u})$ *that solve condition* (6) *with equality; labor market cleaning condition* (10)*; optimization for new tasks* (18)*; land market clearing condition* (A.20) *with arbitrage condition* (A.18)*; and free mobility condition for creators* (20).

The departure from the simple model is summarized as follows, and solutions to the multi-region model are provided in Appendix A.4. Let us consider a location with highly ranked universities where θ_i is large, and there is a positive shock in the location such that the productivity of developers (Λ_i) increases.[14] Then, the arbitrage condition for investors implies a higher return

[13] Note that Equation (20) holds with inequality if $L_i^c = 0$. In the following discussion, we suppose that all locations have a positive number of creators so that Equation (20) is satisfied for all locations.

[14] In our model, an increase in developers' productivity Λ_i is isomorphic to an increase in the locational amenities.

from investment in universities (λ_i). Therefore the set of tasks available in the location expands as new tasks in $[1, K]$ emerge from investment. This has two implications: first, this increase in the number of tasks leads to a lower price index of high-skilled services because more differentiated high-skilled services based on new tasks lower the price index; second, the shock increases the relative wage of creators to workers ($1/\omega_i$) as in Proposition 2. Together, these endogenous mechanisms imply a higher real income ($\mathbb{W}_i^c$) for creators in the economy, which attracts more creators from other regions to the region.

In turn, this attraction of creators further accelerates structural transformation in terms of the labor shift toward services via the mechanism summarized in Section 4.4. In addition, in the three sectors model here, we note that an increase in aggregate income in the location can lead to a larger demand for low-skilled services. This mechanism continues until the housing price (Q_i) becomes sufficiently high in the location so that creators are dispersed across locations. In a nutshell, there is a *positive feedback* between the emergence of new tasks and the rise of services, which results from a positive impact on universities. We will quantitatively evaluate this relationship in the next section.

6 Conclusion

The rate of structural transformation from manufacturing to services varies significantly across regions in the US. To understand such variation, this paper highlights how universities can fuel the rise of services in the local economy. Exploiting datasets on local labor markets and universities in the US, we document several novel empirical facts. First, commuting zones with universities—especially those with higher-ranked ones—exhibit a stronger rise in employment and number of establishments in services. Second, the variation of structural transformation across regions is mainly explained by changes in task contents within each sector. Third, commuting zones with universities saw relatively higher wage premiums for college-educated workers in the past four decades. Lastly, new tasks predominantly emerge in regions with a university.

Guided by these novel facts, we present a new theory of local structural transformation that features heterogeneous task distributions across sectors, endogenous skill-task assignment, and skill premium. In our theory, universities play two important roles in the local labor market: the supply of high-skilled workers and the creation of new tasks via innovative research. Both roles are important in explaining the transition from manufacturing to services but have distinct effects on the skill-task assignment and skill premium, which allows us to distinguish the relative importance of each role. In particular, our theoretical result suggests that it's the innovation role that can jointly account for the higher growth in services and skill premiums in regions with universities.

In the quantitative model, the mobility of high-skilled workers provides an additional channel through which universities affect local structural transformation. In ongoing work, we aim to quantify how universities have shaped the variation in local structural transformation that we observe in the US data, which carries important policy implications.

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Online Appendix for "Universities and the Rise of Services"

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A Theoretical Appendix

A.1 A Closed Economy

Preferences. Individuals' preferences are the same between workers and creators, and preference for consumption of services is captured by CES aggregation in differentiated services with an elasticity of substitution η: $X = \int x(j)^{1-\eta} dj$. The demand for a differentiated service is $x(j) = [p(j)/P]^{-\eta} \alpha \mu Y$, where $P = \left[\int p(j)^{1-\eta} dj\right]^{1/(1-\eta)}$ is ideal price index and Y is aggregate income.

Price of services. The cost of producing one unit of service using creators' task σ in $[1, K]$ as the highest index of tasks is:

$$\gamma(\sigma) = \int_0^{\sigma^*} \frac{w^n}{z^n(\sigma')} d\sigma' + \int_{\sigma^*}^{\sigma} \frac{w^c}{z^c(\sigma')} d\sigma', \tag{A.1}$$

where, on the right-hand side, the first term is the input costs of tasks performed by workers and the second term is those performed by creators. Since differentiated services are one-to-one, corresponding to the index of tasks between $[1, K]$, the index for services is exchangeable to tasks. Therefore, the unit price for a service σ is $\gamma(\sigma)$.

Given the equilibrium task assignment σ^*, price of services increasing and convex in σ: $\gamma'(\sigma) = w^c/z^c(\sigma) > 0$, and $\gamma''(\sigma) = -\gamma'(\sigma) z^{c\prime}(\sigma)/z^c(\sigma) > 0$. In addition, for a given σ, the price of services is independent of the marginal change in the threshold σ^*, $d\gamma(\sigma)/d\sigma^* = 0$. Intuitively, the marginal change of σ^* shifts inputs from tasks produced by creators to those by workers, and they are offset.

Then corresponding price index for services and expenditure share across differentiated ser-

vices are given by:

$$P = \left[\int_1^K \gamma(\sigma)^{1-\eta} d\sigma\right]^{1/(1-\eta)}, \quad x(\sigma) = \frac{\gamma(\sigma)^{1-\eta}}{\int_1^K \gamma(\sigma')^{1-\eta} d\sigma'} \tag{A.2}$$

With the price of services fixed, there is a love of varieties since the price index decreases as K increases. In addition, given prices, we have $\epsilon'(\sigma) < 0$.

Labor market clearing. For both manufacturing and services, firms are competitive and their production function exhibits constant return to scale. Therefore, the labor market clearing condition for workers is:

$$w^n L^n = \underbrace{\alpha(1-\mu)Y\overline{\beta}(\sigma^*)}_{\text{Man. labor demand}} + \underbrace{\alpha\mu Y \int_1^K x(\sigma') \overbrace{\left[\int_0^{\sigma^*} A(s,\sigma')ds\right]}^{\text{Exp. share by service firm } \sigma'} d\sigma'}_{\text{Service labor demand}} \equiv \Gamma^n(\sigma^*, K)Y \tag{A.3}$$

Similarly, we have:

$$w^c L^c = \alpha(1-\mu)Y[1-\overline{\beta}(\sigma^*)] + \alpha\mu Y \int_1^K x(\sigma') \left[\int_{\sigma^*}^K A(s,\sigma')ds\right] d\sigma' \equiv \Gamma^c(\sigma^*, K)Y \tag{A.4}$$

for creators. In this expression, we use $\overline{\beta}(\sigma) = \int_0^\sigma \beta(\sigma')d\sigma' \leq 1$ for the expenditure share of manufacturing firms on tasks up to the task indexed by σ.

$\Gamma^n(\sigma^*, K)$ and $\Gamma^c(\sigma^*, K)$ are continuous functions in σ^*. Taking the ratio of equations (A.3) and (A.4), we obtain the wage curve $\Gamma(\sigma^*, L^c/L^n, K)$ displayed in equation (10) of the main text:

$$\Gamma(\sigma^*, L^c/L^n, K) = \frac{\Gamma^n(\sigma^*, K)}{\Gamma^c(\sigma^*, K)} \frac{L^c}{L^n} \tag{A.5}$$

Equilibrium. On the right-hand side of equations (A.3) and (A.4), we have:

$$\begin{aligned} \int_1^K x(\sigma') \left[\int_0^{\sigma^*} A(s,\sigma')ds\right] d\sigma' &= w^n \int_1^K \frac{x(\sigma')}{\gamma(\sigma')} \left[\int_0^{\sigma^*} \frac{1}{z^n(s)} ds\right] d\sigma', \\ \int_1^K x(\sigma') \left[\int_{\sigma^*}^K A(s,\sigma')ds\right] d\sigma' &= w^c \int_1^K \frac{x(\sigma')}{\gamma(\sigma')} \left[\int_{\sigma^*}^K \frac{1}{z^c(s)} ds\right] d\sigma' \end{aligned} \tag{A.6}$$

Then, the wage curve can be written as:

$$\Gamma\left(\sigma^*, \frac{L^c}{L^n}, K\right) = \frac{\alpha(1-\mu)\overline{\beta}(\sigma^*) + \alpha\mu w^n \int_1^K \frac{x(\sigma')}{\gamma(\sigma')} \left[\int_0^{\sigma^*} \frac{1}{z^n(s)} ds\right] d\sigma'}{\alpha(1-\mu)[1-\overline{\beta}(\sigma^*)] + \alpha\mu w^c \int_1^K \frac{x(\sigma')}{\gamma(\sigma')} \left[\int_{\sigma^*}^K \frac{1}{z^c(s)} ds\right] d\sigma'} \frac{L^c}{L^n} \tag{A.7}$$

In summary, a condition for the task production is:

$$\frac{w^n}{w^c} = \frac{z^n(\sigma^*)}{z^c(\sigma^*)} \equiv \mathcal{Z}(\sigma^*), \tag{A.8}$$

and the labor market clearing condition is:

$$\frac{w^n}{w^c} = \frac{\Gamma^n(\sigma^*, K)}{\Gamma^c(\sigma^*, K)} \frac{L^c}{L^n} \tag{A.9}$$

We can see that $\Gamma(0, L^c/L^n, K) = 0$ and $\Gamma^c(\sigma, K) \to 0$, therefore $\Gamma(\sigma, L^c/L^n, K) \to \infty$ if $\sigma \to K$. The right-hand side $\mathcal{Z}(\sigma)$ of equation (A.8) is a decreasing function, and $\Gamma(\sigma, L^c/L^n, K)$ is increasing in σ given the number of workers and creators and frontier K. Then, there exists a unique cutoff of task σ^* and wage ratio ($\omega = w^n/w^c$) that solve equations (A.8) and (A.9) together. Note that without loss of generality, we can normalize the wages of workers in a closed economy. In particular, we can let $w^n = 1$ denote the wage of workers and $w^c = 1/\omega$ for that of creators. Then, the price of services $\gamma(\sigma)$ is determined by equation (A.1) and the price index P is determined by equation (A.2).

Comparative statics in Proposition 2. **[Part (i)]** It is straightforward to see the impact of relative change in the mass of creators to workers, L^c/L^n. Since the wage curve $\Gamma(\sigma, L^c/L^n, K)$ increases in L^c/L^n for all tasks σ and given K, the upward shift of the wage curve leads to an increase in relative wage ω and expansion of task set for workers, $[0, \sigma^*]$. **[Part (ii)]** Next, we consider the task dissemination for workers. Suppose that $\mathcal{Z}(\sigma)$ changes to $\widetilde{\mathcal{Z}}(\sigma)$ as follows: there exists $\widetilde{\overline{\sigma}} > \overline{\sigma}$ such that $\widetilde{\mathcal{Z}}(\widetilde{\overline{\sigma}}) = 0$, and $\widetilde{\mathcal{Z}}(\sigma) > \mathcal{Z}(\sigma)$ for any $\sigma < \widetilde{\overline{\sigma}}$. Intuitively, this is captured by the rightward shift of the relative productivity curve in Figure 9 of the main text. As a result, we have an increase in the wage ratio (ω) and task threshold (σ^*). This is illustrated in the left-hand panel of Figure 10 in the main text. **[Part (iii)]** Lastly, we consider the change in K, the frontier of tasks. Suppose that the frontier changes from K to $\widetilde{K} > K$. We have:

$$\frac{d\Gamma^n}{d\sigma} = \alpha(1-\mu)\beta(\sigma) + \alpha\mu \int_1^K x(\sigma')A(\sigma, \sigma')d\sigma', \quad \frac{d\Gamma^c}{d\sigma} = -\frac{d\Gamma^n}{d\sigma}$$

For the existing tasks $\sigma \in [0, K]$, the expenditure share $x(\sigma)$ decreases when the task set expands to $[0, \widetilde{K}]$ since expenditure share on services based on incumbent tasks becomes small to expense for new services based on the newly introduced tasks ($\widetilde{K} - K$). Therefore, the marginal increase in $d\Gamma^n/d\sigma$ and marginal decrease in $d\Gamma^c/d\sigma$ become small. Therefore, the wage curve becomes flat *ceteris paribus*. In addition, this change leads to an expansion of the set of tasks performed

by workers $[0, \sigma^*]$, and more tasks are performed by workers. This leads to expenditure share on tasks used by services based on incumbent tasks smaller or equal to the *ex ante*, $A(\sigma, \sigma')$. Since the wage curve always satisfy $\Gamma(0, L^c/L^n, \widetilde{K}) = 0$, the wage curve becomes flat and shifts down for all $\sigma \in (0, K]$. Together with the relative productivity curve $\mathcal{Z}(\sigma)$, we see that wage ratio ω^* decreases and the threshold of tasks σ^* increases to the new level $\widetilde{\sigma}^*$ in equilibrium. Workers perform tasks in $[0, \widetilde{\sigma}^*]$ and creators perform tasks in $[\widetilde{\sigma}^*, \widetilde{K}]$. This is illustrated in the right-hand panel of Figure 10 in the main text.

Sectoral employment for Proposition 3. In the model, the mass of labor inputs in the service sector equals the mass of workers and creators producing tasks used for the service sector. In this point of view, rewriting equations (A.3) and (A.4), the mass of labor inputs in the service is given by:

$$E_{\text{Service}} = \alpha\mu \left[\int_1^K \frac{x(\sigma)}{w^n} \left(\int_0^{\sigma^*} A(\sigma', \sigma) d\sigma' \right) d\sigma + \int_1^K \frac{x(\sigma)}{w^c} \left(\int_{\sigma^*}^K A(\sigma', \sigma) d\sigma' \right) d\sigma \right] Y, \tag{A.10}$$

where we combine the labor inputs for tasks below σ^* (the first term) and tasks between σ^* and K (the second term). Plug equations (A.6) into the right-hand side of equation (A.10), we obtain:

$$E_{\text{Service}} = \alpha\mu \left[\frac{\int_1^K \frac{x(\sigma)}{\gamma(\sigma)} \left(\int_0^{\sigma^*} \frac{w^n}{z^n(\sigma')} d\sigma' \right) d\sigma}{w^n} + \frac{\int_1^K \frac{x(\sigma)}{\gamma(\sigma)} \left(\int_{\sigma^*}^K \frac{w^c}{z^c(\sigma')} d\sigma' \right) d\sigma}{w^c} \right] Y \tag{A.11}$$

Using equation (A.1), the cost of producing one unit of service based on the task in frontier K is:

$$\gamma(K) = \int_0^{\sigma^*} \frac{w^n}{z^n(\sigma')} d\sigma' + \int_{\sigma^*}^K \frac{w^c}{z^c(\sigma')} d\sigma' \tag{A.12}$$

We use this in equation (A.11) to obtain:

$$E_{\text{Service}} = \alpha\mu \left(\int_1^K \frac{x(\sigma)}{\gamma(\sigma)} d\sigma \right) \frac{\gamma(K)}{w^c} \left[1 + \frac{1}{\gamma(K)} \left(\int_0^{\sigma^*} \frac{w^n}{z^n(\sigma')} d\sigma' \right) \left(\frac{w^c}{w^n} - 1 \right) \right] Y, \tag{A.13}$$

which in turn implies the service employment share in the closed economy is:

$$\frac{E_{\text{Service}}}{L^n + L^c} = \alpha\mu\bar{w} \left(\int_1^K \frac{x(\sigma)}{\gamma(\sigma)} d\sigma \right) \frac{\gamma(K)}{w^c} \left[1 + \frac{1}{\gamma(K)} \left(\int_0^{\sigma^*} \frac{w^n}{z^n(\sigma')} d\sigma' \right) \left(\frac{w^c}{w^n} - 1 \right) \right] \tag{A.14}$$

We rearrange this to obtain the expression of the change in labor share as input of services displayed in equation (11) of Proposition 3 in the main text.

A.2 New Tasks

We introduce *investors* to endogenize the set of available tasks in each location. In the absence of investment, the frontier of the tasks in location i is defined as $K_i = 1$. The number of potential investors in the economy determines the number of tasks to be added beyond the index $K_i = 1$ through investment. In the economy, one unit of investment can generate $\phi(\sigma)$ units of new tasks for those with an index of $\sigma > 1$.[A.1] We assume that the return on investment decreases in the complexity of tasks: $\phi'(\sigma) < 0$. Intuitively, complex tasks with higher indices are difficult to create.

Investment in each task requires fixed costs. To add a new task with an index $\sigma > 1$, the fixed cost for investors is given by $G(f, \theta_i)$, where f is a positive constant and θ_i captures the existence of the university. When a university is present in the location, θ_i is strictly positive, and it is zero otherwise. The level of universities is represented by the value of θ_i. Therefore, the fixed cost of adding new tasks is lower when the location has a university, and a large value of θ_i implies a lower cost with a highly ranked university. Investors compete for the opportunity to invest in location i by placing bids, and we denote these bids as π_i.

Now, consider the decision of investors. The investor will invest in the location i if the total profits from adding tasks are greater than zero, namely,

$$\max_{v \geq 0} \left\{ \int_0^v \left[\lambda_i \phi(\sigma) - G(f, \theta_i) \right] d\sigma - \pi_i \right\} > 0 \tag{A.15}$$

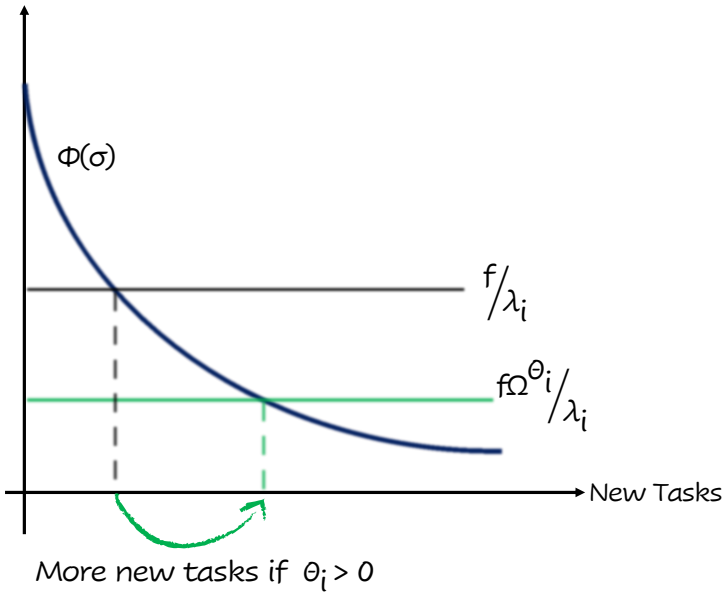
where λ_i is the value of return on investment for each task in location i. Profit maximization of investors in (A.15) determines the creation of new tasks in each location that solve:

$$\phi(v_i) = \frac{1}{\lambda_i} G(f, \theta_i) \tag{A.16}$$

Consequently, the frontier task in location i is given by $K_i = 1 + v_i$. The bid, π_i, is determined by the zero profit condition for investors. The frontier of the task in the economy depends on the value of return from investment λ_i and the existence of universities in the location. Given the function of task creation ϕ, fixed costs f, and the return of investment λ_i, there is a unique index for the frontier of tasks in each location. A location with a higher-ranking university (larger θ_i) exhibits a higher index for the frontier task, and a higher return on investment leads to a higher index for the frontier task.

[A.1] Throughout this section, we assume that the investment, including fixed costs, is in the form of homogeneous goods that are traded in international markets.

Figure A.1: Introducing New Tasks When University Exists



A.3 Housing Market and Mobility

Developers of Housing. Each location has a competitive developer who provides housing. Developers produce housing using homogeneous goods m_i and land for housing development $\mathcal{O}_i$. Their production technology is given by: $H_i = b_i m_i^{\varsigma} \mathcal{O}_i^{1-\varsigma}$, where b_i is location characteristics, $\varsigma \in (0,1)$ is the share of homogeneous goods in the production of housing, and $1-\varsigma$ is the share of developed land. Given the price of housing Q_i and land $\mathcal{O}_i$, developers choose the input of homogeneous goods to maximize their profit. Therefore, the housing supply in location i is:

$$H_i = \Lambda_i Q_i^{\varsigma/(1-\varsigma)} \mathcal{O}_i \tag{A.17}$$

where $\Lambda_i = \xi_i^{1/(1-\varsigma)} \varsigma^{\varsigma/(1-\varsigma)}$. Developers bid for land for construction, and in turn, the bid rent for developed land extracts profit from developers.

Inverstors. As we discussed in Appendix A.2, the return from investment on new tasks for investors in location i is λ_i. However, investors have another option in the economy. In particular, investors invest a unit of homogenous good per unit of land in each location i, and after the investment, the land becomes available for developers. Therefore, Developers bid land rent, which, as a result of investor arbitrage, equalizes the return from land investment with the return from investing in new tasks, namely,

$$\lambda_i = r_i = (1-\varsigma)\Lambda_i Q_i^{1/(1-\varsigma)}, \tag{A.18}$$

where r_i is the bid rent of developers per unit of land.

Mobility. Creators ($\ell = c$) are freely mobile across locations, while workers ($\ell = n$) are not able to move. Given the preference (5), the free mobility of creators implies that their indirect utility is equalized across locations:

$$\mathbb{W}_i^c = \frac{w_i^c}{P_i^{\alpha\mu} Q_i^{1-\alpha}} = \overline{u}, \quad \forall\, i \tag{A.19}$$

where $\overline{u}$ is given in the economy.[A.2] Intuitively, housing prices rise in tandem with wage growth and the influx of creators to a location such as San Francisco, acting as a dispersion force in the economy.

The total expenditure in each location i equals the sum of income of workers and creator, and the market clearing condition for housing implies that total expenditure on land is given by:

$$r_i \mathcal{O}_i = (1-\varsigma)(1-\alpha)(w_i^c L_i^c + w_i^n L_i^n) \tag{A.20}$$

A.4 General Equilibrium for Heterogeneous Locations

Summary. The equilibrium is determined by (i) the set of parameters, including parameters in preference (α, μ, η); parameters in production of manufacturing goods $\beta(s)$; parameters in the task creation (f, Ω), parameters in development of housing (ρ); (ii) the set of fundamental productivity in production and creation of tasks, $\{z^n(\sigma), z^c(\sigma), \phi(\sigma)\}$; (iii) the location fundamentals, including mass of workers (L_i^n); housing constraints (ξ_i); land endowment (T_i); universities (θ_i); and (iv) the total number of creators in the country, $\overline{L}^c$. Given the set of exogenous primitives, the equilibrium is characterized by the following endogenous variables: wage of workers and creators (w_i^n, w_i^c), the mass of creators (L_i^c), the task assignment (σ_i^*), the frontier of tasks (K_i^*), housing prices (Q_i) and the common real income $\overline{u}$.

Solution. We guess wages $\{w_i^n, w_i^c\}$ and mass of creators $\{L_i^c\}$ across locations. First, given the relative productivity $z^n(\sigma)$ and $z^c(\sigma)$, we can solve for the task assignment rule:

$$\omega_i \equiv \frac{w_i^n}{w_i^c} = \frac{z^n(\sigma_i^*)}{z^c(\sigma_i^*)} \tag{A.21}$$

In location i tasks indexed by $\sigma < \sigma_i^*$ are performed by workers and other tasks are performed by creators. When locations i and i' show $\omega_i < \omega_{i'}$, we have $\sigma_i^* > \sigma_{i'}^*$. Since location i has

[A.2] Note that Equation (A.19) holds with inequality if $L_i^c = 0$. In the following discussion, we suppose that all locations have a positive number of creators so that Equation (A.19) is satisfied for all locations.

lower wages for workers relative to creators, a larger number of tasks are assigned to workers in equilibrium.

Second, the land market cleaning condition and arbitrage condition for investors imply:

$$\lambda_i = r_i = \frac{(1-\rho)(1-\alpha)Y_i}{T_i} \tag{A.22}$$

for the return of investment a_i and price of developed land r_i. Then, the optimization of investors in the task creation leads to the number of tasks added in location i:

$$\phi(v_i^*) = \frac{f\Omega^{\theta_i}}{\lambda_i} \tag{A.23}$$

where f is the fixed cost of adding each task and θ_i is the location characteristics of universities. The number of tasks v_i^* is uniquely determined when $\phi' < 0$ and the frontier of tasks is given by:

$$K_i^* = 1 + v_i^* \tag{A.24}$$

When location i exhibits a larger value of $\theta_i > 0$, we obtain a larger number of new tasks, v_i^*, and the higher frontier K_i^*. This is illustrated in Figure A.1 in the main text.

Third, the price of services is determined by the producers' price of services and price index:

$$\gamma_i(\sigma) = \int_0^{\sigma_i^*} \frac{w_i^n}{z_i^n(\sigma')} d\sigma' + \int_{\sigma_i^*}^{\sigma} \frac{w_i^c}{z_i^c(\sigma')} d\sigma', \quad P_i = \left[\int_1^{K_i^*} \gamma_i(\sigma)^{1-\eta} d\sigma \right]^{1/(1-\eta)} \tag{A.25}$$

and expenditure share across different services:

$$x_i(\sigma) = \frac{\gamma_i(\sigma)^{1-\eta}}{\int_1^{K_i^*} \gamma_i(\sigma')^{1-\eta} d\sigma'} \tag{A.26}$$

These variables are determined by the wages $\{w_i^n, w_i^c\}$, the threshold of task assignment σ_i^* and the frontier of tasks K_i^*.

Fourth, we exploit the labor market cleaning condition. Given the mass of workers L_i^n, we obtain the wage of workers using:

$$w_i^n L_i^n = Y_i \left[\alpha(1-\mu)\overline{\beta}(\sigma_i^*) + \alpha\mu \int_1^{K_i^*} x_i(\sigma) \left(\int_0^{\sigma_i^*} A_i(s,\sigma) ds \right) d\sigma \right], \tag{A.27}$$

where the right-hand side is the total expenditure of manufacturing firms and service firms on tasks produced by workers. This leads to the wage for workers as a function of the initial guess of the mass of creators and wages: $\widetilde{w}_i^n$. Analogously, we can compute wage for creators given the

initial guess, $\widetilde{w}_i^c$. Furthermore, combining the labor market cleaning conditions for workers and creators yields:

$$L_i^c = \frac{w_i^n}{w_i^c} \frac{\alpha(1-\mu)\left[1-\overline{\beta}(\sigma_i^*)\right] + \alpha\mu \int_1^{K_i^*} x_i(\sigma) \left(\int_{\sigma_i^*}^{K_i^*} A_i(s,\sigma) ds \right) d\sigma}{\alpha(1-\mu)\overline{\beta}(\sigma_i^*) + \alpha\mu \int_1^{K_i^*} x_i(\sigma) \left(\int_0^{\sigma_i^*} A_i(s,\sigma) ds \right) d\sigma} L_i^n \tag{A.28}$$

Therefore, we obtain the demand for creators as a function of the initial guess of the mass of the mass of creators and wages: $\widetilde{L}_i^c$.

Fifth, with the competitive developers in the housing market, housing prices are:

$$Q_i = \rho^{-\rho}(1-\rho)^{-(1-\rho)} \frac{r_i^{1-\rho}}{\xi_i} \tag{A.29}$$

Therefore, there is a one-to-one mapping from land prices to housing prices. The real income of creators becomes:

$$\mathbb{W}_i^c = \frac{w_i^c}{P_i^{\alpha\mu} Q_i^{1-\alpha}} \tag{A.30}$$

This pins down the level of common real income in the country, $\overline{v}$. We update the guess of wages and mass of creators.

B Data Appendix

B.1 Imputation and Crosswalks

The CBP data only provides the number of establishments within a certain range of employment. We first estimate the true values of all missing employment using the disclosed ones through recursive regressions following Acemoglu et al. (2016). Then, we adjust the imputed employment for hierarchical consistency by proportionally expanding or shrinking the employment and apportioning employment in establishments that miss detailed industry codes (i.e., employment in the parent industry was greater than its child-level total) so that higher-level industries consist solely of missing employment in subordinate totals. Then, we assign the grouped industries to the lowest-level subordinate industries (6-digit for NAICS and 4-digit for SIC). We then gradually change all industrial codes to 1987 SIC while doing the assignment again before each conversion.

Apart from some outliers mentioned in the original code of Acemoglu et al. (2016), there were still some underlying issues with the raw data from years earlier than 1986. For certain early years,

Table B.1: Summary Statistics: CBP vs ACS

	1980 CBP	1980 ACS	1990 CBP	1990 ACS	2000 CBP	2000 ACS	2010 CBP	2010 ACS	2016 CBP	2016 ACS
Number of Commuting Zones										
Total	734	699	721	688	740	722	740	722	739	722
With College	429	421	422	413	429	427	429	427	429	427
Without College	305	278	299	275	311	295	311	295	310	295
Manufacturing Sector Employment Share										
Average	0.29	0.25	0.21	0.20	0.16	0.16	0.11	0.11	0.10	0.11
Standard Deviation	0.006	0.004	0.005	0.004	0.004	0.003	0.003	0.002	0.004	0.002
With College	0.29	0.25	0.20	0.20	0.15	0.16	0.11	0.11	0.10	0.11
Without College	0.32	0.21	0.28	0.20	0.22	0.19	0.15	0.13	0.15	0.14
Service Sector Employment Share										
Average	0.64	0.59	0.73	0.64	0.77	0.69	0.83	0.74	0.83	0.74
Standard Deviation	0.005	0.003	0.005	0.003	0.004	0.002	0.003	0.002	0.003	0.002
With College	0.64	0.59	0.73	0.64	0.78	0.69	0.83	0.75	0.83	0.75
Without College	0.57	0.55	0.64	0.60	0.69	0.60	0.76	0.67	0.76	0.66

Note: CZs are defined as 1990 Commuting Zones. Average and standard deviation of sector employment shares are calculated as the mean and standard deviation across CZs in a given year. "With College" and "Without College" represent the CZs with and without a four-year or above college in the IPEDS data.

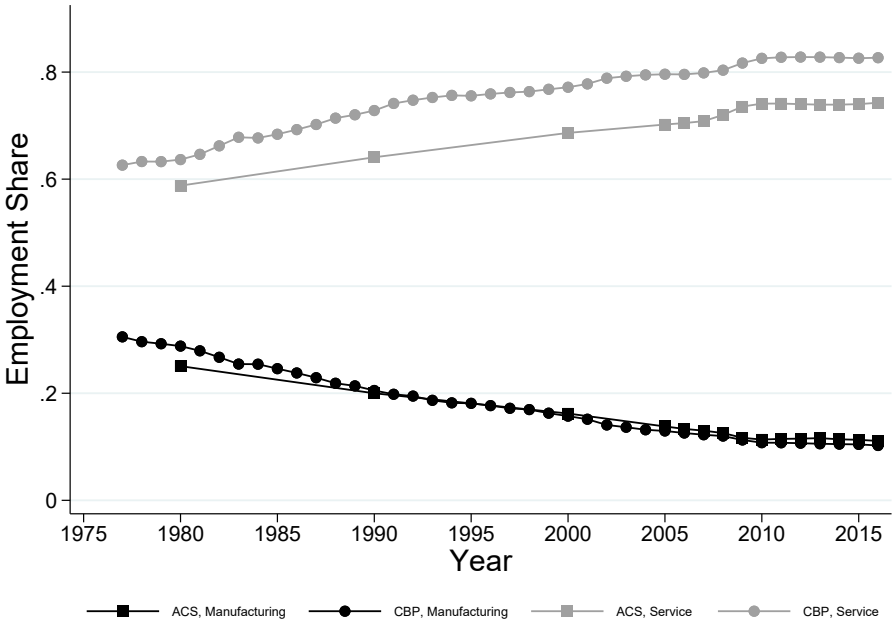
the total number of establishments was inconsistent with the sum of all ranges, so we replaced the totals with these sums. Additionally, the estimated average employment in each establishment did not always fall within its corresponding range. We overlooked this issue because the subsequent code ensured that the imputed values fell within their bounds. Similar to the years after 2006, employment in a parent-level industry may be lower than its child-level total. We treated this as a statistical error and replaced the parent-level employment with its child-level total to apportion employment as mentioned above.

B.2 Summary Statistics

Table B.1 provides summary statistics of employment from the CBP and ACS for selected years across CZs in the US. The data include the number of CZs and employment shares in the manufacturing and service sectors. We further disaggregate these statistics based on the presence of a four-year college within the CZs. Our CBP and ACS data have a similar coverage of CZs reflected in the number of CZs in each dataset, which shows minor fluctuations over time. The number of CZs with a college presence also remains relatively stable over the years and is comparable

across the two samples.

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

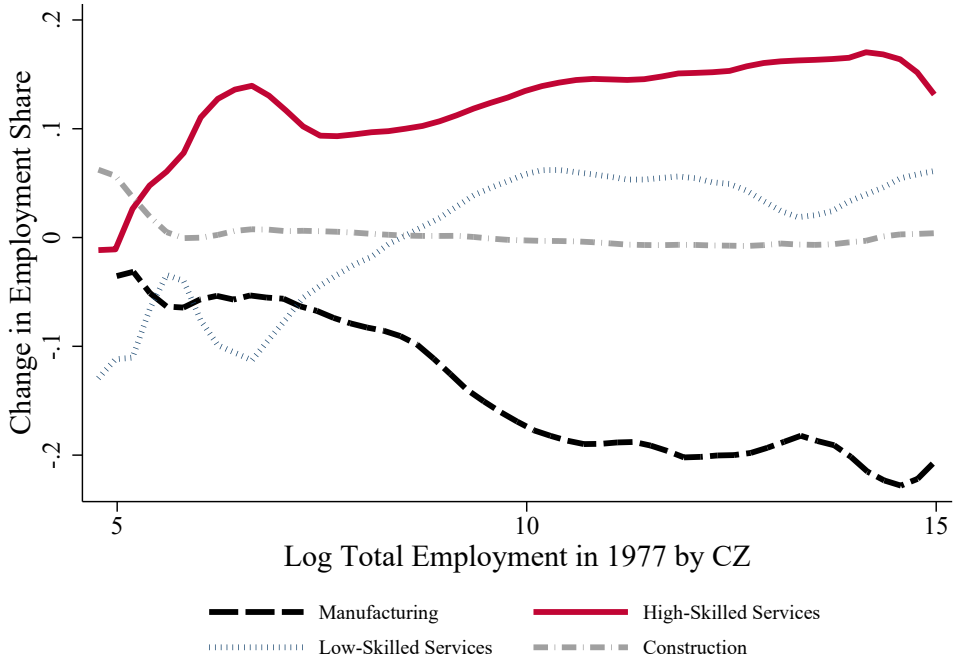


Note: This figure plots the average share of employment in manufacturing and services across CZs using ACS and CBP data between 1977 and 2016.

C Additional Empirical Results

C.1 Additional Supporting Descriptive Facts

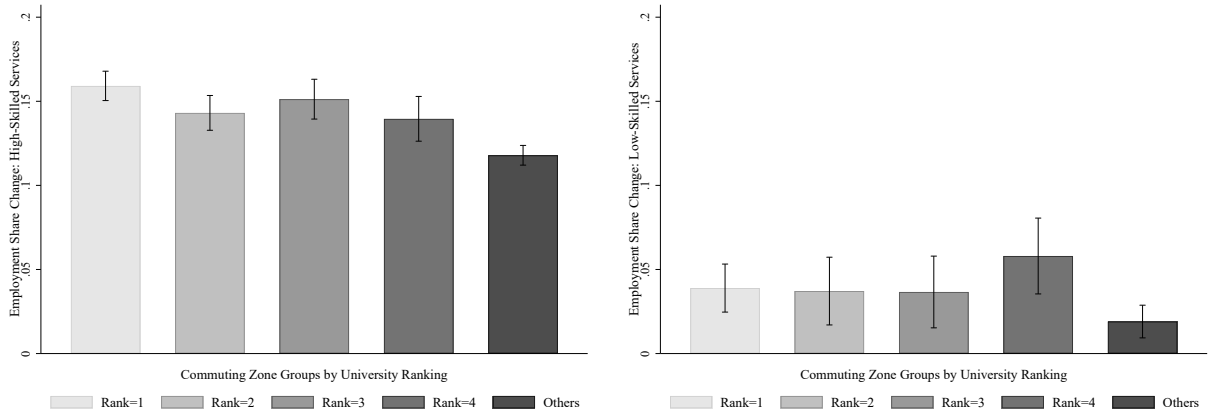
Figure C.1: Change in Employment Share by Sector and CZ: 1977-2016



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

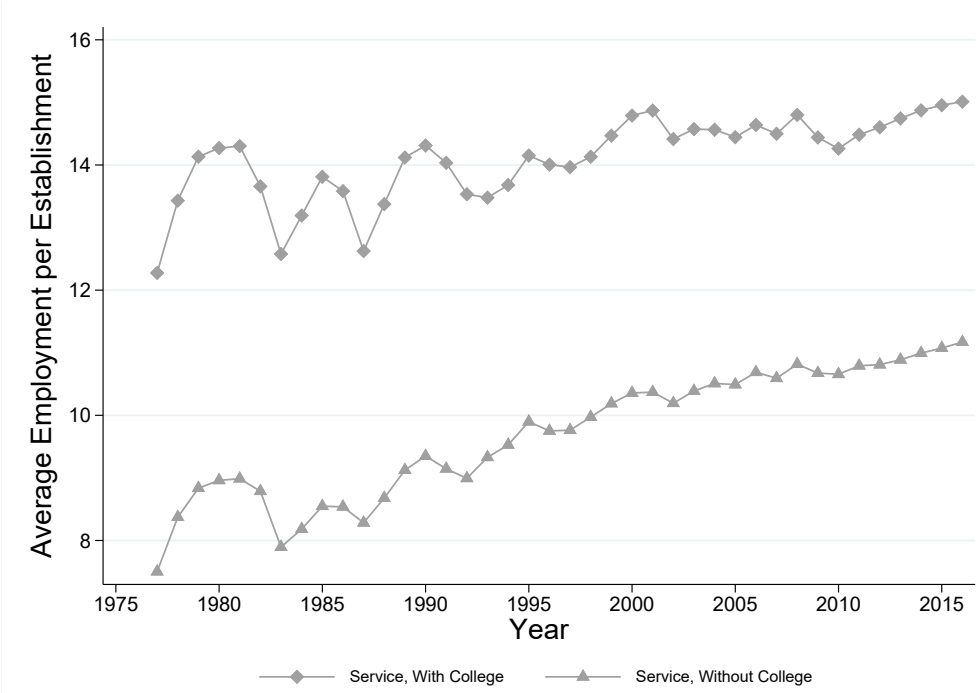
In Figure C.2, we categorize CZs into five groups based on the ranking of the top university in each CZ, where "Rank=1" corresponds to the group containing the top 100 universities according to the US News ranking. We find that CZs with a top 100 university experienced the most rapid increase in service sector employment share. In addition, structural transformation is significantly more pronounced in CZs that have a university included in our ranking list (i.e., the top 440 universities) compared to those without a ranked university, which are classified as "Others."

Figure C.2: Change in Service Employment Share Across Commuting Zones



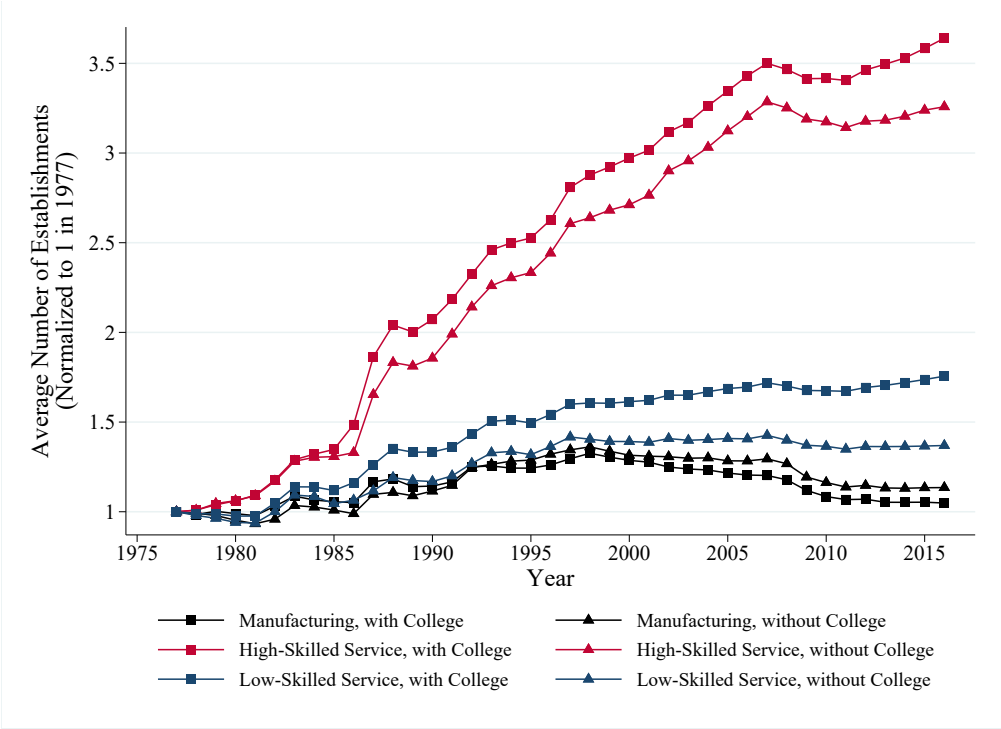
Note: These figures show the average employment share changes for high-skilled and low-skilled service sectors between 1977 and 2016 across CZs, grouped by the existence of a four-year university in that region. The bars represent the average change in service employment share in each group, and the vertical lines represent their 95 percent confidence intervals. Data sources are CBP and IPEDS.

Figure C.3: Average Size of Establishments in Services



Note: This figure plots the average employment per establishment in the service sector across CZs with or without college between 1977 and 2016. Each point is the average employment size in the group of CZs by the existence of a four-year university. The data source is CBP.

Figure C.4: Average Number of Establishments by Sector and Location



Note: This figure plots the changes in average number of establishments by sector across CZs with or without college between 1977 and 2016, with 1977 data normalized to one. The red, navy, and black lines represent high-skilled service, low-skilled service, and manufacturing sectors respectively. Within a sector, squares (triangles) are the average number of establishments in that sector for CZs with (without) a four-year university. The data source is CBP.

C.2 Additional Evidence on Identification using College Site-Selection Data

Table C.1 presents the regression results when we consider locations initially selected for colleges as "winners," even though the colleges were later relocated away from these sites. Estimated effects do not change a lot, with only small improvements in p-values.

Table C.1: Effects of winning a college site selection

	(1) Manufacturing	(2) Service
Winning site	-0.010**	0.012**
	(0.028)	(0.012)
1977 sectoral employment share	-0.621***	-0.629***
	(0.000)	(0.000)
1977 total employment	-0.013***	0.019***
	(0.000)	(0.000)
Constant	0.150***	0.375***
	(0.000)	(0.000)
Observations	943	945

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$