Universities and the Rise of Services*

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January 8, 2026

Incomplete and Preliminary

Abstract: Structural transformation from manufacturing to services varies widely across regions. Using regional data from the US, we document four stylized facts: (i) commuting zones with universities experience higher growth in service employment and establishments, especially high-skilled services; (ii) the college wage premium is higher in commuting zones with universities; (iii) structural transformation within tasks and skills is the primary driver of the differential growth of services across regions; and (iv) new tasks emerge predominantly in places with universities. We develop a task-based theory of local structural transformation in which universities function as talent hubs that supply high-skilled labor, and innovation hubs that create new tasks and increase the demand for skills. Our theory and quantitative analysis suggest that the innovation role jointly accounts for the higher growth in services and the skill premium in regions with universities. Our framework provides microfoundations for skill-biased structural change and highlights the role of higher education in shaping regional economic dynamics.

Key words: structural transformation, skill premium, innovation, economic geography

JEL classification: R11, O11, I25

*We thank Enrico Berkes, Henry Chen, David Dorn, Shoya Ishimaru, Taylor Jaworski, Junmin Liao, Ralf Meisenzahl, Tommaso Porzio, Diego Restuccia, Richard Rogerson, conference/seminar participants at Urban Economic Association (UEA), WAMS, SMU-Jinan CURE, EFG Meeting, and NBER Summer Institute for useful discussions. Liu acknowledges Singapore MOE AcRF Tier 1 Grant (FY2023-FRC1-004) for financial support. Tze Hao Lim, Zihui Wang and Weiheng Zheng provided excellent research assistance. All errors are ours. Liu: Department of Economics and Risk Management Institute, National University of Singapore. E-mail: charlesliu.pku@gmail.com. Takeda: Department of Economics, National University of Singapore & Centre for Economic Performance, London. AS2, 1 Arts Link, Singapore 117570, E-mail: k.takeda@nus.edu.sg.

1 Introduction

Structural transformation of the macroeconomy from manufacturing to services has been extensively studied, yet much less is known about how this transformation unfolds unevenly across regions within a country. Consider Detroit and Pittsburgh: both cities were historically reliant on manufacturing, yet they have experienced different economic trajectories in recent decades. Detroit, once the heart of the American automotive industry, has struggled to adapt to the service-oriented economy, resulting in economic decline and population loss. In contrast, Pittsburgh, once dependent on steel manufacturing, successfully transformed itself into a center for education, healthcare, and technology. These divergent outcomes raise a fundamental question: what drives the geographic variation in structural transformation?

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

In this paper, we ask whether and how universities in the local economy contribute to the structural transformation from the traditional manufacturing to the modern service economy. We present evidence that universities have a positive impact on the growth of the service sector by studying the variation in the rise of services across US regions. In particular, regions with top universities are associated with higher growth of employment and establishments in services, higher skill premiums, and the emergence of new tasks. We then develop a simple theory of structural transformation in the local economy and show that universities' contribution to the innovation of new tasks is crucial to understanding their role in the growth of the service sector. This process expands the variety of services and drives demand for high-skilled workers who specialize in tasks intensively used in high-skill services.

We begin by documenting a substantial variation in structural transformation trends across US commuting zones (CZs). While the majority of CZs experienced positive growth in the rise of services over the past four decades, we observe substantial geographic variation. Areas in the Northeast such as Boston and New York, the West such as the Silicon Valley, and the South such as Austin show some of the most significant increases in service sector employment. In contrast,

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

parts of the Midwest and interior regions lagged behind, experiencing more modest gains or even declines. Importantly, this variation cannot be attributed solely to differences between large and small cities or between urban and rural areas. Instead, these patterns are strongly correlated with the spatial distribution of colleges using data from the Integrated Postsecondary Education Data System (IPEDS). Motivated by this observation, we present several novel empirical findings linking local structural transformation to the presence of universities.

First, regions with four-year colleges have seen faster growth in the share of service sector employment. 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. Conditional on the initial size of employment and sectoral employment composition, CZs with higher-ranked top universities had the most substantial growth in the high-skilled service sector. In particular, 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 suggests that the growth in service sector employment has been associated with an increase in the number of establishments, particularly in CZs with colleges.

To address the endogeneity of university locations, we exploit the natural experiment of college site selections back in the 1800s following Andrews (2023) and Russell, Yu, and Andrews (2024) and identify the impact of universities. Comparing the winning and the runner-up counties in the same college-site selection experiment, we find that the former counties have shown a larger increase in service employment in the recent four decades. This suggests that the presence of universities itself shapes the geographically differential rise of services rather than economic size, initial economic structure, and local amenities, which are simply correlated with the presence of a university.

Next, we analyze the relationship between universities and local labor market dynamics, focusing on the evolution of skill premium and the emergence of new tasks, using data from the American Community Survey (ACS). Our findings are twofold. First, we find that the college/skill premium increased more in regions with a university than in those without. Since 1990, CZs with universities have consistently exhibited higher skill premiums, suggesting that these areas have been the key drivers of the national rise in the return to skill. 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) and on urban-rural disparities in skill premium (e.g., Glaeser and Maré, 2001; Gould, 2007; Baum-Snow and Pavan, 2012) by highlighting the role of universities in shaping the regional variation of skill premium.

Second, we show that the emergence of new tasks in response to technological innovation, as documented by Autor et al. (2024), is disproportionately concentrated in regions with universities. For instance, the occupation of "computer systems analysts and scientists" saw a surge in new job titles around 1990, reflecting the broader expansion of the IT sector. Employment share of this occupation is significantly higher in CZs with a university. Overall, we find that occupations with a large share of new job titles in the last decades are concentrated in CZs where a university exists. This pattern suggests that universities not only supply skilled labor but also play a central role in the creation and diffusion of new tasks.

To connect the local labor market dynamics in skills and tasks to local structural transformation, we decompose the change in the employment share of services at the CZ level into two components: (i) changes in the skill components that are accompanied by the assignment of skills to tasks, and (ii) structural change within task and skill. Intuitively, (i) captures the growth in skilled labor supply relative to the low-skilled, say, as a result of higher education expansion, whereas (ii) captures an example in which high-skilled workers as technicians in the automotive industry in the 1970s transitioned to developers in high-tech services in the 2000s. Our decomposition shows that the latter accounts for the majority of the geographic variation in structural transformation between 1970 and 2015, whereas changes in the skilled labor supply contribute marginally.

These two channels roughly correspond to the dual role of universities: first, as local *talent hubs* that produce high-skilled labor; and second, as local *innovation hubs* that foster the development of new tasks, particularly within emerging service industries. Our reduced-form evidence suggests that the innovation channel accounts for much of the geographic variation in the expansion of the service sector. Innovation and high-skilled graduates from universities, especially top-tier ones, create new tasks and services. This increases employment opportunities and new business establishments, thereby accelerating structural transformation. We formalize and evaluate these mechanisms through a simple theoretical framework and a quantitative spatial model.

The simple theory links differential skills, tasks, and sectors and shows how universities shape the difference in local structural transformation via the two new channels discussed above. 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 the two types of workers. The manufacturing and services sectors 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 the assignment rule of tasks to workers and the wage ratio between high and low-skilled workers, given their relative sizes and the set of tasks.

Our theory predicts that regions transform from manufacturing to services at different rates when they have different patterns in (i) supplying high-skilled workers, and (ii) creating new tasks. This implication illustrates the role of universities in explaining the local structural transformation as suppliers of high-skilled workers *and* hubs for innovating new tasks. For example, top US universities in Silicon Valley and the Research Triangle have pumped high-skilled engineering and computer science graduates into the local economy and also created new tasks and industries, such as researchers in AI and social network services. 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 low-skilled worker tasks.

Importantly, 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). An increased supply of high-skilled workers shifts tasks from low-skilled to high-skilled workers but lowers the skill 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 regions with universities predominantly drive the rising skill premium suggests that the innovation effect may outweigh the talent supply effect.

To quantify the mechanisms through which universities shape the local rise of services, we extend the stylized 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. The mobility of high-skilled workers across regions establishes 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 is associated with more differentiated services, which lowers the total price index. Moreover, the 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 increases their supply, accelerating 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.

This paper contributes to the literature on structural transformation by documenting new facts about its geographic variation within a country. The shift from agriculture to manufacturing and then to services has been extensively studied in the macroeconomic literature, e.g., Fisher (1939); Kuznets (1966); Barro and Sala-i Martin (2004); Buera and Kaboski (2012); Herrendorf, Rogerson, and Valentinyi (2014), and various mechanisms explain structural transformation in the aggregate economy, including exogenous productivity growth (e.g., Baumol 1967; Matsuyama

1992; Laitner 2000; Ngai and Pissarides 2007; Huneeus and Rogerson 2024) and non-homothetic demand across sectors (e.g., Kongsamut, Rebelo, and Xie 2001; Matsuyama 2009; Comin, Lashkari, and Mestieri 2021). At the sub-national level, Caselli and Coleman II (2001) studies aggregate structural transformation and regional convergence together; Desmet and Rossi-Hansberg (2009, 2014) develop a model of technology diffusion to investigate the spatial pattern of structural transformation; Eckert and Peters (2022) studies 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. Fulford and Schiantarelli (2024), XXX. In this paper, we focus on 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 model, which is applied to labor research, such as Acemoglu and Autor (2011), to study how different skill groups perform imperfectly substitutable occupations.[2] We view the expansion of tasks in our theory as similar to the idea of product diversity along with structural transformation (Romer 1987; Ciccone and Matsuyama 1996; Fafchamps and Helms 1996). In addition, the approach has been supported by evidence that points to an increasing number of workers in new work in locations initially dense with college graduates (Lin 2011) and the positive association between new job titles and employment growth in US (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. Among others, our theory is reminiscent of Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2022), which present task-based models to understand the effects of automation and new tasks. Yet, our model focuses on the effect of introducing new tasks and the spatial variation of its impact on structural transformation.[3]

Add Hanson and Moretti (2025).

Lastly, this paper contributes to the literature examining the role of universities in regional economic growth (see for example, Valero and Van Reenen 2019; 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 (Carneiro, Liu, and Salvanes 2023), the relationship between human capital and regional development (see for example, Acemoglu and Dell 2010; Gennaioli

[2]The task-based approach in the labor market is defined by Autor, Levy, and Murnane (2003) and it is related to job polarization with a reduction of routine jobs (Goos and Manning 2007). In recent, Acemoglu and Restrepo (2019) point out that automation can increase total labor demand if it creates new tasks for workers.

[3]In this respect, our theoretical framework offers a micro foundation for the "skill-biased structural change," which is often exogenously assumed in existing models (Buera et al. 2022).

et al. 2013), and the interaction of education and innovation in driving aggregate productivity (Akcigit, Pearce, and Prato 2025). This paper presents (i) new empirical evidence on the impact of universities on the structural transformation in the local economy from manufacturing to services and (ii) a simple theory and quantifiable model for connecting the location of universities and the geographic variation in structural transformation and college wage premiums.

The rest of this paper proceeds as follows. Section 2 details the data used in our empirical analysis. In Section 3, we present new facts relating universities to the regional growth of service employment and skill premium. In addition, we decompose the structural transformation to understand the sources of its geographical variation. Section 4 develops a new theoretical framework of the assignment model of skills, tasks, and sectors and discusses universities' role in local structural transformation. The theory is extended to a multi-region economy in Section 5, which is calibrated using US data in Section 6. In Section 7, we calibrate the model to quantify the mechanisms underlying local structural changes. Finally, Section 8 concludes.

2 Data

In this section, we describe the datasets used in our empirical analysis and provide descriptive statistics of the overall and regional structural transformation in the US, together with 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). CBP data for the period 1986–2016 were obtained from the U.S. Census Bureau, while data for 1977–1985 were sourced from the ICPSR.[4] Following the imputation method in Acemoglu et al. (2016), we construct a dataset of annual county and CZ-level employment and establishment counts at the 4-digit 1987 SIC industry level. Although the CBP data provide broad coverage of firms across local labor markets and industries, they do not include detailed micro-level information on wages or the occupational and skill composition of the workforce—factors essential for analyzing local economic conditions beyond aggregate measures. To address this limitation, we supplement the CBP data with aggregated individual-level information from the ACS. Using the survey-provided individual weights, we compute average annual wages and total employment by geographic location, industry, occupation, and educational attainment.[5] Appendix Table D.1 demonstrates that

[4] 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.

[5] Our analysis is restricted to individuals who were actively employed and worked between 50 and 52 weeks in the prior year.

employment measures from the ACS are broadly comparable to those from the CBP, despite the former being based on individual-level survey responses. Figure D.1 further illustrates the close alignment between the two sources in capturing broad trends in structural transformation. This consistency allows us to leverage the richer occupational and skill-level detail available in the ACS to conduct a more granular analysis of changes in structural transformation.

Sectors We primarily focus on three sectors throughout this paper: manufacturing (SIC 2000–3999), high-skilled services, and low-skilled services. Our definition for high vs low-skilled service sectors broadly follows the literature (for example, Buera et al., 2022), with the former including "Finance, Insurance and Real Estate (FIRE)," "Business Services," "Health Services," "Legal Services," "Educational Services," "Engineering, Accounting, Research, Management, and Related Services," and the latter including the remaining service sectors such as "Retail Trade" and "Personal Services." Where necessary, we also examine the service sector, which combines both high-skilled and low-skilled services, and the construction sector, defined by SIC codes 1500–1799.

Occupations and Skills We obtain data on local and industry-level occupations and skills from from ACS for the years 1950, 1970, 1980, 1990, 2000, and annually from 2005 to 2016, which are available in IPUMS. These individual-level survey data provide detailed information on educational attainment, employment status, occupation, industry, and wage income. To classify occupations, we adopt two complementary approaches. First, following Autor and Dorn (2013), we categorize occupations into "abstract," "routine," and "manual" based on their task intensity. Second, we employ the Nam-Powers-Boyd scores,[6] which quantify occupational skill intensity. In our context, "skill" is proxied by educational attainment at the individual level; for example, a college graduate is assumed to possess higher human capital than a high school graduate. To assess the role of universities, we construct a binary skill indicator equal to one for individuals who have completed a four-year college degree or higher, and zero otherwise. We then aggregate the individual-level data by county or commuting zone (CZ) within each occupation and skill category to generate measures of total local employment and average local wages by occupation-skill cell.

Universities Data on US universities are drawn from the Integrated Postsecondary Education Data System (IPEDS), which covers the universe of accredited higher education institutions from 1980 to 2022, excluding the years 1981 to 1983. We construct a panel dataset by merging annual files using each institution's unique identifier. The resulting dataset includes rich institutional-level information on location, type, enrollment, graduation rates, and financial metrics such as grant disbursements and expenditures. Given our focus on the role of universities in generating

[6] Available at http://www.npb-ses.info/.

high-skilled labor and facilitating task creation, we broadly classify institutions into four-year colleges and all others. To proxy for institutional quality, we categorize universities based on their rankings in the 2016 U.S. News & World Report Best National Universities list.[7] While historical rankings are not consistently available, we use the 2016 rankings as a proxy for institutional quality over time, given the relative stability of rank groupings despite annual fluctuations in individual positions. The ranking includes approximately 440 institutions, which we group into five categories: "Rank 1" (ranks 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 harmonize the raw data using standardized classification systems for geographic location, industry, and occupation, following the crosswalks developed in Autor and Dorn (2013) and Autor, Dorn, and Hanson (2019).[8] For geographic harmonization, we map Census State Economic Areas, Census County Groups, and ACS Public Use Micro Areas to 1990 CZs, which forms our baseline geographic regions.[9] Industries are converted into a unified 1987 Standard Industrial Classification (SIC) 4-digit code system using a weighted crosswalk procedure. Occupational codes from the Census (*occ*) are mapped to the *occ1990dd* classification as in Autor and Dorn (2013). The resulting regional panel dataset contains, for each CZ, information on industry, occupation, skill (education), employment, wages, and the number of establishments. In addition, we include a binary indicator for the presence of a four-year college ("college" dummy), and a categorical variable capturing the rank group of the highest-ranked university within the region.

2.2 Descriptive statistics

These data offer valuable insights into local economic dynamics over the past decades. To begin, we present descriptive facts on national and local sectoral employment shares derived from both CBP and ACS data, along with the spatial distribution of colleges categorized by ranking group.

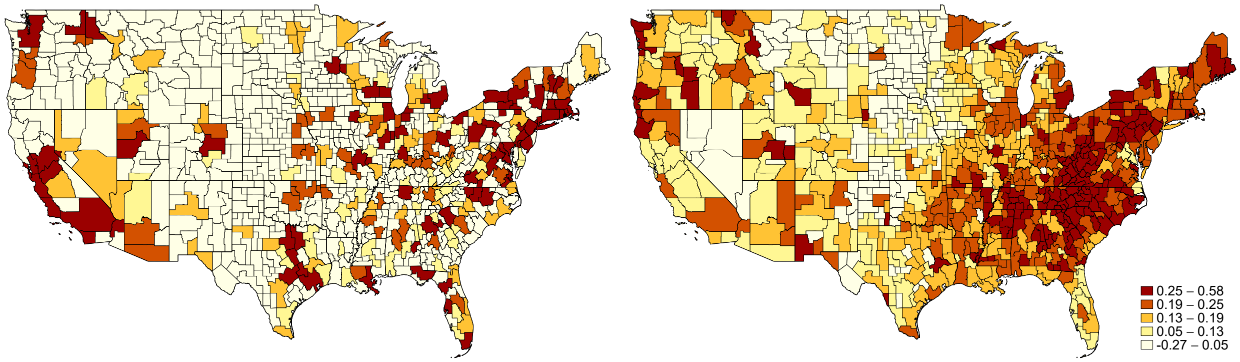
First, consistent with a large body of literature, our regional data reveal clear patterns of aggregate structural transformation from manufacturing to services. Employment in the manufacturing sector declined markedly between 1980 and 2016, with average employment shares falling from approximately 0.29 to 0.10 across both the CBP and ACS data. CZs lacking a four-year college consistently exhibit higher manufacturing employment shares than those with one, suggesting a potential role of higher education in shaping local labor market compositions. Conversely, the service sector experienced a substantial expansion over the same period, with average employment shares rising from approximately 0.59–0.64 to 0.74–0.83. CZs with a college

[7] Available at https://www.usnews.com/best-colleges/rankings/national-universities.

[8] These crosswalks are available on David Dorn's website https://www.ddorn.net/data.htm.

[9] In exercises that require the use of county-level data, such as in Sec 3, we rely directly on raw CBP data.

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



(a) US Colleges by Rankings

(b) Change in Employment Share of Services

Notes: Panel (a) plots the distribution of colleges by their 2016 US News rankings. CZs in the US are divided into five groups: from dark to light, rank=1; rank=2; rank=3; rank=4; and others. Panel (b) illustrates the change in the service sector employment share between 1977 and 2016 across US CZs, grouped into five quintiles based on the magnitude of the change. Data source: US News Best National Universities Ranking and CBP.

generally display higher service employment shares than those without. These trends not only reaffirm the nationwide shift from manufacturing to services, as widely documented in the literature, but also emphasize the role of higher education in contributing to the spatial heterogeneity of structural transformation—an issue central to our analysis.

Second, the geographic distribution of universities exhibits substantial heterogeneity across regions. Panel (a) of Figure 1 illustrates the spatial allocation of U.S. colleges by rank across CZs in 2016, based on data from the U.S. News Best National Universities Ranking. The map employs a gradient shading scheme, where darker tones denote CZs hosting higher-ranked institutions (Rank 1), and lighter tones indicate zones with lower-ranked universities or none (Rank 5). This spatial visualization highlights pronounced regional disparities in the quality of higher education institutions. Higher-ranked universities are disproportionately concentrated in the Northeastern and Western regions, although several top-ranked institutions are also present in parts of the Midwest and the South.

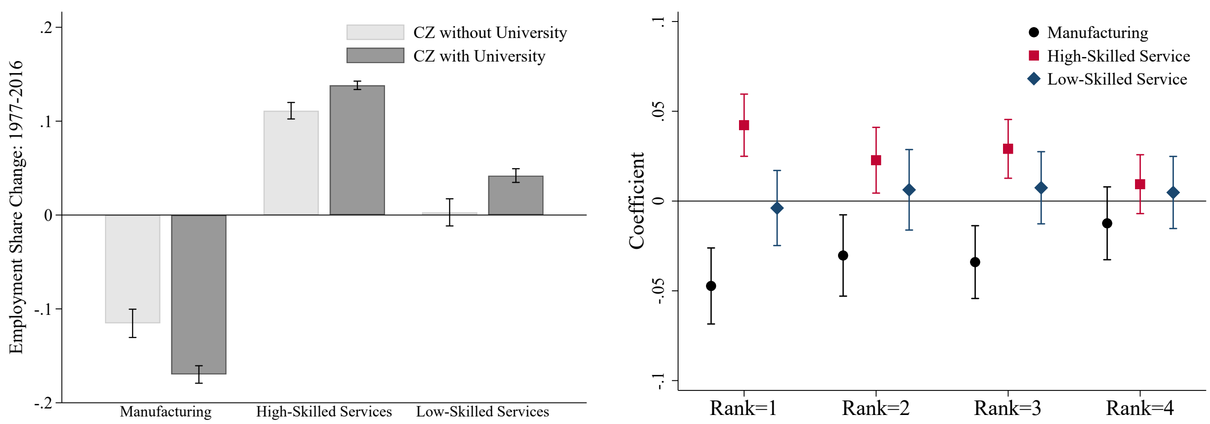
Third, we observe substantial regional variation in the rise of the service sector. Panel (b) of Figure 1 depicts changes in the service sector employment share across CZs from 1977 to 2016. The figure reveals considerable heterogeneity in the magnitude of structural transformation. The Northeast and Mid-Atlantic regions—including metropolitan areas such as New York City, Philadelphia, and Boston—experienced pronounced increases in service employment, with gains exceeding 25 percentage points in some CZs. In contrast, regions in the South, Mountain West, and Great Plains generally saw more modest increases, and in some cases, declines. We hypothesize that the presence of colleges is a key factor driving this regional heterogeneity in structural transformation, a proposition we examine in greater detail in the following section.

3 Motivating Evidence

In this section, we begin by presenting four novel empirical patterns related to local structural transformation and labor markets, which point to a potential role for universities in shaping local economic dynamics. We then leverage historical college site selection experiments conducted between 1839 and 1954 to identify the causal impact of universities on the growth of the service sector. Finally, we decompose the observed changes in service employment shares to isolate the key components driving local structural transformation.

Fact #1: Service Employment Growth is More Pronounced in CZs with Colleges, especially Those with a Top-ranked Institution.

Figure 2: Universities and Local Structural Transformation



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

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

Notes: These figures show the average changes in sectoral employment share between 1977 and 2016 across CZ 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 CZ employment 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 by sector, together with their 95 percent confidence intervals. Data sources: CBP, IPEDS, and US News Best National Universities ranking.

We present descriptive evidence on the heterogeneity of structural transformation across CZs. We begin by comparing CZs based on the presence or absence of a four-year college or university. Panel (a) of Figure 2 displays the average change in sectoral employment shares between 1977 and 2016 for these two groups. Over this period, the average increase in the service sector employment share was 17.8 percentage points in CZs with a university, compared to 11.3 percentage points in those without. This cross-regional disparity is evident in both high-skilled and low-skilled service sectors; however, the growth is concentrated in high-skilled services, while employment shares in low-skilled services remained largely unchanged—particularly in regions lacking a university. In contrast, the manufacturing sector experienced a substantial decline in its employment share, with the decline being more pronounced in CZs that host a university.

Not all universities are alike. We next examine the role of university quality. Moreover, structural transformation may be shaped by other regional characteristics such as population size. In addition, regional differences in initial industrial composition may interact with sectoral shocks—such as increased import competition—in shaping sectoral employment dynamics. To account for these factors, we estimate regressions of changes in employment shares in the manufacturing and service sectors on indicators for the rank of the highest-ranked university in each CZ. The regressions control for total employment and sectoral employment shares in the base year, 1977.

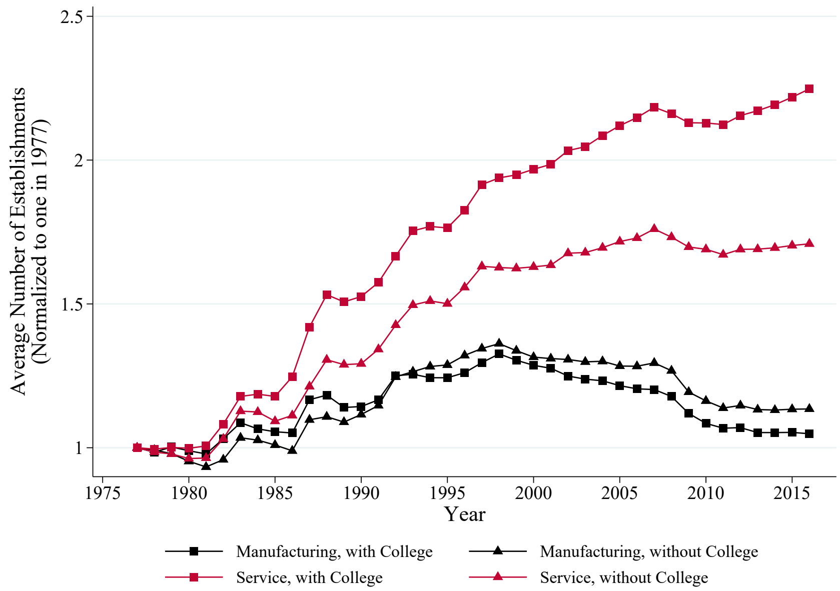
Panel (b) of Figure 2 plots the estimated coefficients on university rank groups, interpreted relative to the omitted category of "Others" (i.e., CZs with the lowest or no ranked university). The results indicate that CZs with higher-ranked universities—particularly those ranked in the Top 300—exhibit statistically significant differences in structural transformation, with larger declines in manufacturing employment and greater increases in high-skilled service employment. In contrast, differences in low-skilled service sector growth across rank groups are minimal. These findings suggest that the presence of a higher-ranked university is associated with a more pronounced shift from manufacturing to high-skilled services, even after accounting for initial employment levels and industrial composition. Our results also highlight that the differential expansion of the service sector across CZs with varying university ranks is primarily attributable to growth in high-skilled service employment. This empirical pattern motivates a differential treatment of high- and low-skilled services in the modeling framework developed in the subsequent analysis.[10]

Fact #2: Number of Service Sector Establishments Grew more Rapidly in CZs with Colleges than Those without. In Contrast, the Number of Manufacturing Establishments Increased Through the Late 1990s Before Entering a Period of Decline.

Figure 3 depicts 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. Establishment counts are normalized to their 1977 levels, facilitating a comparison of growth trajectories over time relative to the base year. The figure reveals distinct sectoral trends and a marked divergence between CZs with and without a college presence, particularly in the service sector, where growth is substantially higher in regions hosting a four-year institution.

[10] College-linked employment may take an exceptional weight in the (high-skilled) service sector in smaller regions, such as small college towns. In Appendix E.1, we show that the result in Figure 2 holds when the education service sector is removed from the sample.

Figure 3: Average Number of Establishments by Location and Sector

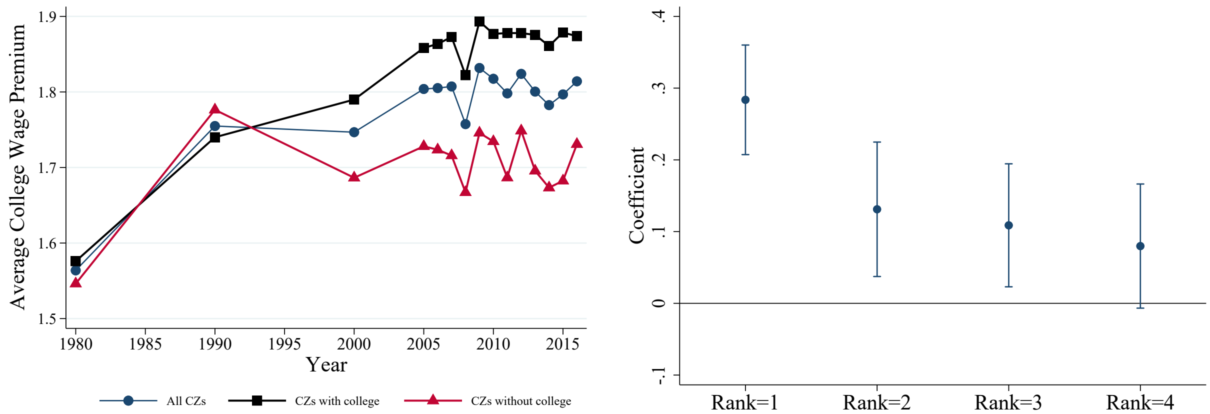


Notes: This figure plots the changes in average number of establishments by sector across CZs with or without college between 1977 and 2016, with 1977 data normalized to one. The red (black) points and lines show the average number of establishments in the service (manufacturing) sector. Within a sector,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

The service sector experienced substantial growth in both groups of CZs; however, the expansion was significantly more pronounced in regions with a college presence. By 2016, the average number of service sector establishments in CZs with a four-year college had more than doubled relative to 1977, indicating robust growth. Although CZs without a college also experienced an increase, the pace of growth was noticeably slower. This divergence suggests a positive correlation between the presence of higher education institutions and the proliferation of service sector establishments, potentially reflecting the higher concentration of skilled labor and innovation-oriented activities typically associated with college towns.

In contrast, trends in the manufacturing sector followed a markedly different trajectory. The number of manufacturing establishments remained relatively stable over the full period, exhibiting minor fluctuations and ultimately returning to levels close to those observed in 1977. Both groups of CZs saw a decline in manufacturing establishments beginning in the late 1990s, consistent with broader structural shifts in the economy away from manufacturing and toward services. Notably, the decline was slightly more pronounced in CZs with a college, further emphasizing the role of educational institutions in shaping the direction and composition of local economic transformation.

Figure 4: Skill Premium Changes by Location



(a) Skill Premium in CZs with and without University

(b) Relative Skill Premium across CZs

Notes: Panel (a) plots the 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. Data source: ACS.

Fact #3: On Average, the Skill Premium Increased 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 extend this well-documented national trend in rising skill premiums by disaggregating CZs based on the presence of a four-year college. In CZs with a college, the skill premium exhibits a clear and persistent upward trajectory throughout the period. Between 1980 and the early 2000s, these regions experienced a steady and faster-than-average increase in the skill premium relative to national trends. Although the upward momentum plateaued following the Great Recession, the skill premium in these CZs remained well above the levels observed in the 1980s and 1990s, as well as above those in regions without a college presence. In contrast, CZs without a college followed a markedly different path. While the skill premium in these regions initially rose at a pace comparable to—or even exceeding—that of CZs with a college, it began to decline around 1990, with only sporadic periods of modest recovery. Since 2000, the skill premium in non-college CZs has consistently lagged behind that of college CZs. The growing divergence between these trajectories over time underscores a widening regional gap in the returns to skill. It also suggests that local labor markets with colleges may have primarily driven the widely documented upward trend in skill premiums.

Similar to the analysis above, we examine how changes in the skill premium vary across regions with universities of differing ranks. Panel (b) shows that between 1980 and 2016, regions hosting universities ranked within the top 300 experienced significantly larger increases in the skill premium compared to those with lower-ranked or no ranked institutions. The most pronounced rise is observed in CZs with top 100 universities. This pattern closely parallels the results on local structural transformation, reinforcing the notion that the quality of higher education institutions plays a critical role in shaping regional labor market dynamics.

Fact #4: New Tasks Emerge Predominantly in Regions with Colleges.

Autor et al. (2024) document that new work emerges in response to technological innovation. We build on their analysis by examining the geographical distribution of new occupation titles. While their dataset provides information on the number of new titles by occupation and year, it does not include employment counts at the title level or the geographic location of these new titles. To address this limitation, we adopt an indirect approach. Specifically, we use Autor et al. (2024)'s data to compute a "new title share" for each occupation-year pair, capturing the relative intensity of new title creation within occupations over time. These shares offer insight into which occupations experienced the greatest influx of new job titles in a given year. We then ask: where are these high–new-title-intensity occupations geographically concentrated?

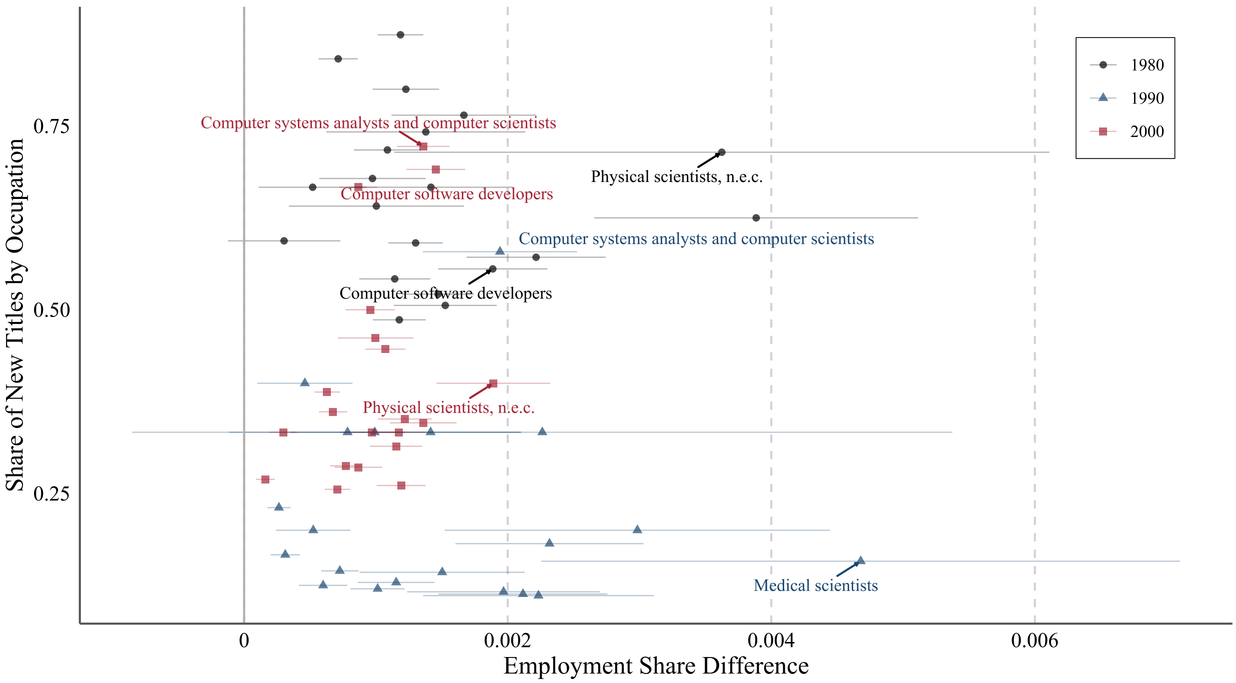
Using occupation-level employment data from the ACS, we estimate differences in employment shares by occupation and year between CZs with and without a university presence. Figure 5 presents the results for the top 20 occupations ranked by their *new title share* for the years 1980, 1990, and 2000. The majority of these occupations exhibit significantly higher employment shares in CZs with universities, indicating that occupations experiencing the most rapid expansion in new job titles tend to be more concentrated in regions hosting higher education institutions. For example, the top-ranked occupation in 1990, *computer systems analysts and scientists*, likely reflects the rapid growth of the IT sector during the 1980s and 1990s. Employment in this occupation is notably higher in CZs with a university than in those without, suggesting that many of the newly emerging job titles within this field are disproportionately located near universities. This empirical pattern motivates our modeling assumption that universities function as hubs of innovation and play a central role in the creation of new tasks.

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

$$\text{New Task}_{it} = \sum_{o} \frac{L_{iot}}{L_{it}} \frac{N_{ot}^{\text{New}}}{N_{ot}}, \tag{1}$$

where the first term, L_{iot}/L_{it}, represents the share of employment in occupation o at location i, computed using ACS data. The second term, $N_{ot}^{\text{New}}/N_{ot}$, captures the new titles share within each

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



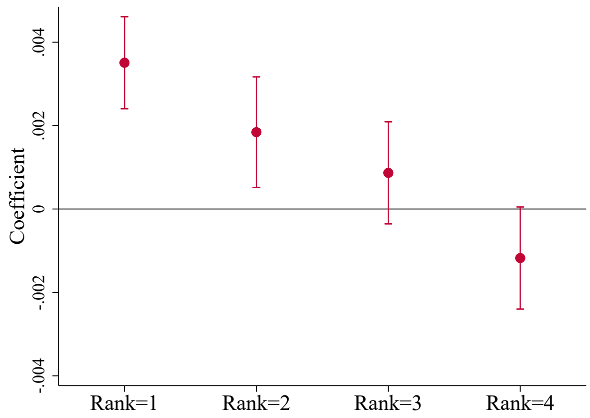
Notes: The vertical axis shows the share of new titles by occupation in the years 1980, 1990, and 2000, using the "New Work" data constructed by Autor et al. (2024). The horizontal axis shows the coefficient estimates for the cross-CZ regression of employment share by occupation on a university dummy.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

occupation o. Conceptually, a location that has many occupations with both high employment share and high new titles share is likely to be where new tasks are concentrated. Our goal is to show whether this index varies with the existence of a (top) university in that region. To do so, we run a regression similar to Panel (b) of Figure 2 and 4, and compare this index across each ranking group. Results for 1990 and 2000 are shown in Figure 6. For both years, CZs with top universities are associated with significantly higher concentration of new tasks, which is consistent with the message conveyed in Figure 5.

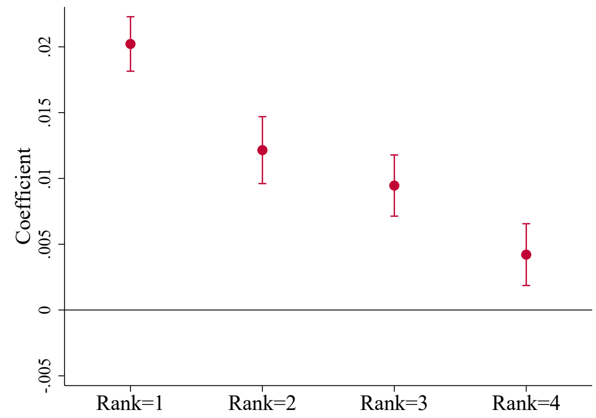
Identifying the impact of universities

A potential concern is the endogeneity of university location. Consequently, the observed differences in structural transformation may be driven by confounding factors unrelated to the causal impact of universities—such as initial economic size, pre-existing industrial structure, or other locational characteristics that are correlated with both the presence of a university and subsequent economic outcomes. To identify the causal impact of hosting a university on local structural transformation, we adopt the empirical strategy proposed by Andrews (2023) and Russell, Yu, and Andrews (2024), which compares counties that were selected to host a university with those that were runners-up in the same site-selection process. These college siting experiments, con-

Figure 6: New-Task Index by Location



(a) 1990



(b) 2000

Notes: These figures show the geographic variation in the "New-Task Index" (1) across CZ groups. 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 this index for 1990 (the left-hand panel) and 2000 (the right-hand panel) on a set of indicators on the rank group of the top university in each CZ. This figure plots the coefficients on these ranking indicators, together with their 95 percent confidence intervals. Data sources: Autor et al. (2024) and US News Best National Universities ranking.

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

	Manufacturing	Service
Winning Site	-0.009**	0.012**
	(0.005)	(0.005)
Sectoral Employment Share in 1977	-0.618***	-0.629***
	(0.036)	(0.038)
Log Total Employment in 1977	-0.013***	0.018***
	(0.002)	(0.002)
Constant	0.149***	0.377***
	(0.024)	(0.032)
Observations	930	932

Notes: This table reports the coefficient estimates of equation (2). Robust standard errors clustered by CZ are shown in parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

ducted between 1839 and 1954, provide plausibly exogenous variation in university placement.[11]

In particular, we estimate the following equation:

$$\Delta \ell_c^j = \beta^j \text{Treatment}_c + \gamma_1^j \ell_{c,1977}^j + \gamma_2^j \log L_{c,1977} + \gamma_e^j + \epsilon_c^j, \tag{2}$$

where j represents the sectors (manufacturing or services). The dependent variable $\Delta \ell_c^j$ is the

[11]In our benchmark analysis, we exclude colleges that were subsequently relocated after the initial site-selection decision. A robustness check including these institutions, using their new locations, yields qualitatively similar results. Details on the data can be found in Appendix E.3.

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 time-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^j stands for the experiment fixed effects so that comparisons are between winning and runner-up counties for the same college. This setup allows for 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. As documented in Andrews (2023) and Russell, Yu, and Andrews (2024), this assumption is likely to hold; in fact, some of these selection experiments were even randomly assigned. Table 1 presents the coefficient estimates together with the standard errors clustered by CZ, considering the potential correlation of economic activities within a region. Our main parameters of interest, β^j, are precisely 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, counties selected to host a university experienced a greater decline in the manufacturing employment share and a larger increase in the service employment share. Moreover, we find that initial economic conditions play a meaningful role in shaping the heterogeneity of structural transformation across counties.

4 A Task-Based 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 by skill and sector. In Subsection 4.1 and 4.2, we lay out the model environment and define the competitive equilibrium. Subsection 4.3 provides comparative statics for the key variables in the model. Subsection 4.4 explains how this simple model provides new insights into structural transformation, which are connected to the empirical findings in Subsection 4.5. Subsection 4.6 discusses how the model mechanism relates to and differs from existing ones in the literature. Further details of the model are presented in Appendix A.

4.1 Setup

We consider a single economy embedded in a large economy. There are two types of agents indexed by $\theta \in \{\ell, c\}$, where superscript ℓ refers to *workers* without a college degree and c stands for *creators* who have received higher education. The total mass of each type in this economy is given by L^ℓ and L^c, respectively. All agents inelastically supply one unit of efficient labor. The labor market is competitive, and wages are given by w^ℓ and w^c for each type of worker. There are two types of products labeled as manufacturing goods and services.The manufacturing goods are homogeneous and freely tradable in a large economy, whereas services are differentiated and nontradable.

Tasks Performed by Individuals Tasks are horizontally differentiated, for example, car assembly, weaving textiles, constructing housing, and AI research. They are indexed by $j \in [0, J]$, where J denotes the upper bound of the set of existing tasks. This set of tasks expands as new tasks are introduced in the economy. Without loss of generality, we assume $J > 1$. Production of these tasks only requires efficient labor: one unit of efficient labor provided by type θ labor produces $z^\theta(j)$ units of task j. Creators can, in principle, perform any task, that is, $z^c(j) > 0$ for all existing tasks. Workers, however, can perform only a subset of tasks. Specifically, there exists $\overline{j} < J$ such that $z^\ell(j) \geq 0$ for tasks in $[0, \overline{j}]$, while $z^\ell(j) = 0$ for tasks $j \geq \overline{j}$. This implies an exogenous upper bound on the set of tasks accessible to workers without higher education: they are unable to perform frontier tasks, such as scientific research.

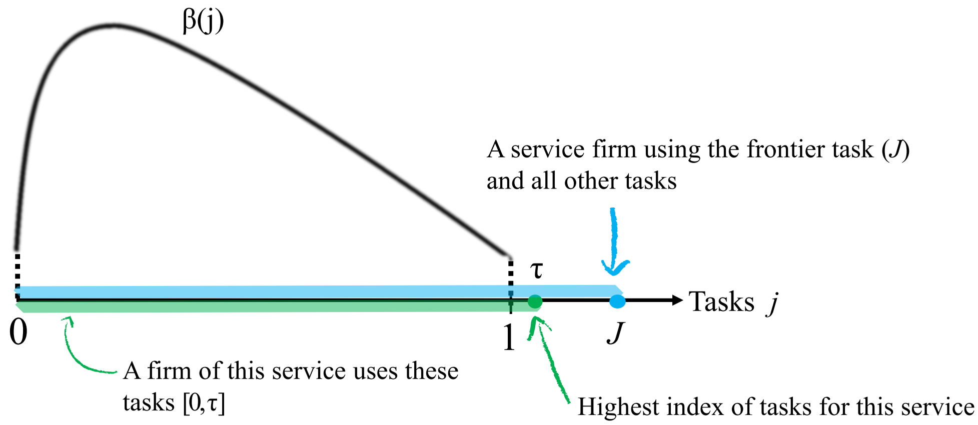
Tasks are ordered such that the relative productivity of workers to creators is decreasing with the task index j. That is, creators have more comparative advantage in the task with a higher j; and vice versa. The market for tasks is perfectly competitive. Unit production cost of task j by worker type θ is: $\gamma^\theta(j) = w^\theta / z^\theta(j)$. Therefore, task j is performed by workers instead of creators if:

$$\omega \leq \frac{z^\ell(j)}{z^c(j)}, \tag{3}$$

where ω denotes the relative wage of workers to creators (w^ℓ / w^c). This condition implies a task assignment rule: lower j tasks are taken by workers and higher ones are performed by creators. The price of each task is given by $\gamma(j) \equiv \min\{\gamma^c(j),\ \gamma^\ell(j)\}$.

Manufacturing Firms A representative firm producing goods combines tasks in the interval $[0, 1]$. This fixed interval of tasks in the production of homogeneous goods is intuitive for traditional goods, which require a fixed set of tasks that always exist. The production technology is Cobb-Douglas, and to produce one unit of manufacturing goods, a firm's expenditure on a specific task j in $[0, 1]$ is given by $\beta(j) \in (0, 1)$. For future reference, we also define the cumulative expenditure share by $\overline{\beta}(j) = \int_0^j \beta(j') dj'$. In Figure 7, the black curve shows an example of the

Figure 7: Tasks in the Production of Manufacturing Goods and Services



expenditure share over tasks used in manufacturing firms.

Service Firms Services are differentiated. There are competitive firms for each service, and their production technology exhibits constant return to scale.[12] Each service firm is characterized by its highest index of tasks, which must be greater than one. In Figure 7, for example, we consider a firm with the highest index of tasks, $\tau \in [1, J]$. We assume that the production of service firms follows a Leontief technology that uses a continuum of tasks $j \in [0, \tau]$. Intuitively, the production of a service exploiting the highest index of tasks τ requires all tasks below τ: an asset management firm in the service sector requires both simple tasks (e.g., cleaning, driving) and more skill-intensive ones (e.g., analyst, manager). The advantage of Leontief technology is that the marginal cost of supplying each service is linear in the marginal cost of each task.

Given the marginal cost of each task $\gamma(j)$, the cost of producing one unit of service characterized by its highest task τ among inputs is equal to the price of the service:

$$p(\tau) = \int_0^\tau \gamma(j)\, dj, \tag{4}$$

and the expenditure share of the service firm on different tasks $j \in [0, \tau]$ in production is:

$$\vartheta(j, \tau) = \frac{\gamma(j)}{\int_0^\tau \gamma(j')\, dj'} = \gamma(j)/p(\tau) \tag{5}$$

Preference We assume that households spend a share α of their income on services and $1 - \alpha$ on manufacturing goods. Within the service sector, each differentiated service is indexed by its

[12]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 $J - 1$. 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.

highest task $\tau \in [1, J]$ used in production. We assume for simplicity the expenditure share on a differentiated service τ is given by $x(\tau, J)$. The expenditure share depends on the index of the service *and* the number of varieties, which is defined by the size of J. Conditional on the number of varieties, the expenditure share decreases in τ: $\frac{\partial x(\tau,J)}{\partial \tau} < 0$. Details on the preferences and the derivation of $x(\tau, J)$ can be found in Appendix A.2.

4.2 Equilibrium

The labor market clearing condition states that labor supply and demand are equal for each type θ. Combining the two equations for the two types of labor, we derive the labor market clearing condition in terms of the relative wages of workers to creators:

$$\omega^* = \frac{(1-\alpha)\overline{\beta}(j^*) + \alpha \int_1^J x(\tau, J) \left[\int_0^{j^*} \vartheta(j,\tau) dj \right] d\tau}{(1-\alpha)\left[1 - \overline{\beta}(j^*)\right] + \alpha \int_1^J x(\tau, J) \left[\int_{j^*}^J \vartheta(j,\tau) dj \right] d\tau} \frac{L^c}{L^\ell} \equiv \Gamma\left(j^*, \frac{L^c}{L^\ell}, J\right), \tag{6}$$

where, α denotes the income share on services; $x(\tau, J)$ the expenditure share on the service indexed by task $\tau \in [1, J]$; and $\vartheta(j, \tau)$ the input share of task $j \in [0, j^*]$ produced by workers in the production of service τ. Derivation of equation (6) is relegated to Appendix A.3. We now formally define the equilibrium for this economy.

Definition 1. *Given the mass of workers (L^ℓ) and creators (L^c), the equilibrium is characterized by the wage ratio of workers to creators ω^* and task assignment j^* that solves condition (3) with equality, and labor market cleaning condition (6).*

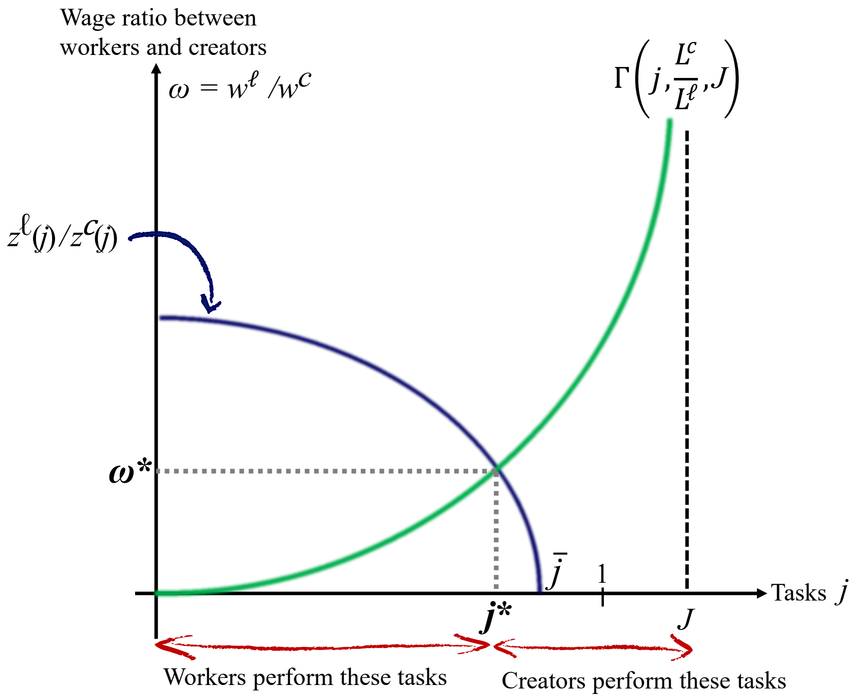
Figure 8 illustrates the competitive equilibrium. The wage curve $\Gamma(j, L^c/L^\ell, K)$ is increasing in task index j and $\lim_{j\to\infty} \Gamma(j, L^c/L^\ell, K) = \infty$. Since the right-hand side of the relative labor productivity of workers to creators in condition (3) is decreasing in j, the threshold of task index j^* and wage ratio ω^* are uniquely determined in equilibrium.

Proposition 1. *Given the mass of workers (L^ℓ) and creators (L^c), we have a unique equilibrium (j^*, ω^*). Tasks indexed by $[0, j^*]$ are performed by workers; and those indexed by $[j^*, J]$ are performed by creators.*

4.3 Comparative Statics: Race between Education and Technology

Our model can be used to study the effects of labor supply, task dissemination and innovation on the local labor market, which are linked to the various roles of a university. To begin with, education increases the number of creators relative to workers, therefore larger L^c/L^ℓ. Ceteris

Figure 8: Equilibrium Illustration



paribus, a stronger supply of creators results in a higher relative wage between workers and creators because of an upward shift of the wage curve: $\Gamma(j, \delta L^c/L^n, J) > \Gamma(j, L^c/L^n, K)$ for any constant $\delta > 1$ and task j. This results in a smaller threshold of task j^* and higher ω^*, as illustrated in Panel (a) of Figure 9. Therefore, we have *downgrading* of tasks for creators together with *lower* skill premium.

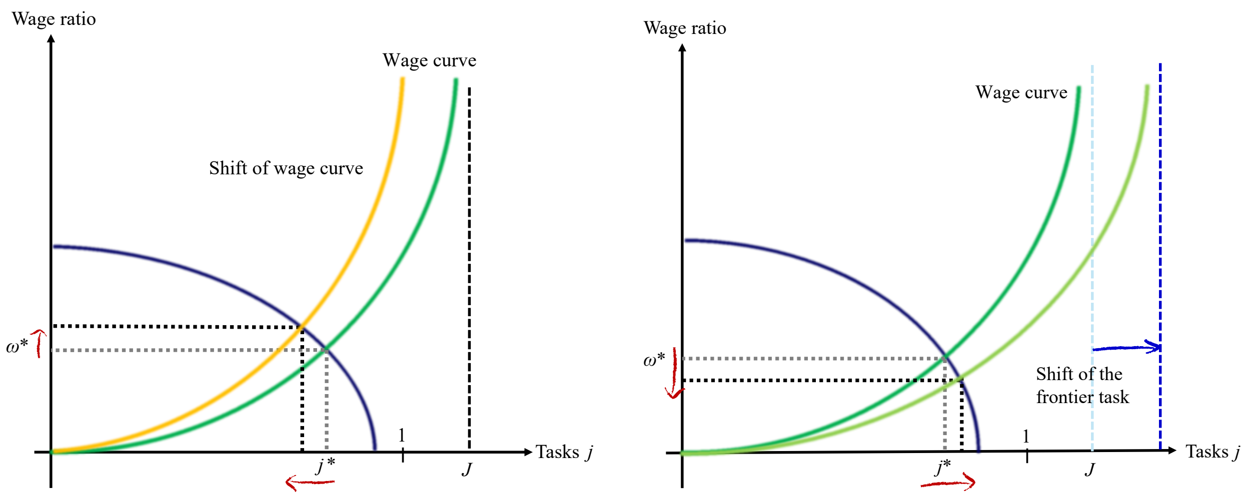
Next, we explore the impact of *innovation* that introduces new tasks to the local labor market, another role of universities suggested by the data findings. Our model captures the emergence of new tasks by a rightward shift in J. While this does not alter the relative productivity of workers, it does cause a shift in the wage curve. Suppose that the wage curve shows:

$$\Gamma\left(j, \frac{L^c}{L^{\ell}}, J\right) > \Gamma\left(j, \frac{L^c}{L^{\ell}}, J + \Delta\right), \quad \forall\, j \in [0, J] \tag{7}$$

where new tasks expand the set of tasks from J to $J + \Delta$. By assumption, the newly created tasks are performed by creators, who have comparative advantages in doing so, and the production of services using those new tasks disproportionately increases the demand for relatively complex tasks (an increase in the denominator of equation (6)). Panel (b) of Figure 9 shows the labor market effect of this *skill-biased innovation in tasks*. As a result, the equilibrium wage ratio ω^* falls: an increase in demand for creators results in a higher skill premium. In addition, the set of tasks performed by workers $[0, j^*]$ expands with creators specializing in more complicated tasks.

Our model can also be used to study the impact on the local labor market if the relative productivity $z^{\ell}(\sigma)/z^{c}(\sigma)$ changes. Workers can adopt new technology that expands the set of

Figure 9: Supply of High-skilled Labor and Innovation of Tasks



(a) Supply of High-skills

(b) Innovation

tasks available to them, captured by an increase in $\overline{\sigma}$. This implies that workers become able to perform tasks for which creators have relatively high productivity. This *dissemination* process increases the relative productivity of workers performing tasks of higher index. In equilibrium, it leads to a higher relative wage ω^* and an expansion of the set of tasks $[0, j^*]$ that workers perform.

The following proposition summarizes these effects:

Proposition 2. (i) *If the ratio of creators to workers* (L^c/L^ℓ) *increases, the wage ratio* ω^* *increases and set of workers' tasks* $[0, j^*]$ *shrinks;* (ii) *If there is skill-biased innovation in tasks that expand the set of tasks from* $[0, J]$ *to* $[0, J + \Delta]$ *with* (7)*, the wage ratio* ω^* *decreases and the set of workers' tasks* $[0, j^*]$ *expands; and* (iii) *If dissemination of technology for workers is accompanied by an increase in* $\overline{j}$*, the wage ratio* ω^* *increases and the set of workers' tasks* $[0, j^*]$ *expands.*

A formal proof of this proposition is provided in Appendix A.4. 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. In what follows, we focus on the case in which innovation of creating new tasks is skill-biased and satisfies (7), given the number of workers and creators.

4.4 *The Rise of Services*

We now use the model to illustrate how and why services grow in the local economy. Specifically, we examine the labor used in services and discuss how it's driven by different factors.[13] The mass of labor inputs in the service sector equals the mass of workers and creators producing tasks used for the service sector, namely,

$$E_{\text{Service}}\left(\omega^*, j^*;\ J\right) = \underbrace{(1-\omega^*)\left(\int_0^{j^*} \frac{1}{z^\ell(j)}dj\right) D_{\text{Service}}}_{\substack{\text{Labor demand for workers} \\ \text{performing tasks for services}}} + \underbrace{\omega^* p(J) D_{\text{Service}}}_{\substack{\text{Labor demand for creators} \\ \text{performing tasks for services}}}, \tag{8}$$

where D_{Service} is the aggregate demand of services.

The first term represents the demand for workers who perform tasks over $[0, j^*]$, which is employed by service firms that produce services indexed by $j \in [1, J]$. The labor demand for workers increases as their relative compensation becomes more cost-effective to perform the same task when the wage ratio ω decreases. The second term captures the demand for creators in the production of services, which increases when the wage of creators (w^c) is low given the production cost of the frontier services $p(J)$. Then, we obtain the following proposition:

Proposition 3. *Given demand, task reallocation from creators to workers associated with lower wage ratio ω leads to an increase in the employment share of services.*

The proof is relegated to Appendix A.4. The intuition of Proposition 3 is as follows. First, the demand for workers who perform tasks used in services increases. Second, the input costs of all service firms, including frontier service, decrease as a result of the increased number of tasks performed by workers, given the set of services and wages. The relative effect of them is determined by the level of relative wages (ω), so overall employment in services increases if the wage ratio is sufficiently small.

Now consider the effects of an innovation that increases the frontier of the tasks (J), given the demand schedule for services D_{Service}. An increase in J impacts service jobs in four ways: first, advancing the frontier lowers relative wages and reallocates tasks from creators to workers; second, it hinges on whether workers doing new tasks are assigned to services or manufacturing; third, innovation results in the emergence of new firms that provide new services, thereby increasing the need for tasks involved in their production; fourth, the cost associated with producing new services changes compared to the creator's wage, affecting the demand for creators.

Among the four channels above, the first three are associated with an increase in service employment, and the last effect is non-negative if an increase in the production cost of the frontier

[13] Given the total number of creators and workers is fixed, an increase in labor for services implies a higher employment share for services.

service $p(J)$ dominates an increase of wage premium $(1/\omega)$, namely, $\omega_1^* p(J_1) > \omega_0^* p(J_0)$ for $J_0 < J_1$. Then the demand for creators who perform tasks intensively used in the frontier services increases. This effect relies on the shape of creators' productivity. We summarize the results in the following Proposition 4:

Proposition 4. *Given the demand schedule, the introduction of new tasks into the frontier from J_0 to J_1 increases the employment share of services when the production cost of the frontier service $p(J)$ increases more than wage premium: $\frac{p(J_1)}{p(J_0)} \geq \frac{1/\omega_1^*}{1/\omega_0^*}$. The effects are more pronounced if demand for the frontier service increases and more tasks are reallocated from creators to workers.*

We also show that creating new tasks results in an increase in the within-sector labor composition. In particular, more workers work in the manufacturing sector, while more creators work in the service sector. This effect is independent of the change in prices of services but depends on the rightward shift of the threshold j^* and decrease in wage ratio ω^*.

Proposition 5. *The introduction of new tasks at the frontier increases the share of workers in the manufacturing sector and the share of creators in the service sector.*

Taken together, these results show that the innovation of new tasks can be an important factor underlying the rise of the services and the decline of the manufacturing sector. It is associated with a skill-biased shift within the service sector through the task reallocation as well as a higher skill premium.[14] We now turn to discuss the implications of universities in the process.

4.5 The Roles of Universities: Linking Theory with Empirical Facts

Based on Propositions 2 to 4, we derive the theoretical implications of a university presence on the rate of structural transformation and relate them to the facts documented in Section 3.

First, universities are the hubs of talent, which supply high-skilled individuals with college degrees. Following Proposition 2 (i), this force should have led to a lower wage premium for creators. By contrast, the college wage premium has increased over time, especially in regions with colleges, as evidenced by Fact 3 in Section 3. In addition, an increase in the supply of creators results in the reallocation of tasks from workers to creators, i.e., smaller j^*. By equation (8), a reduction in wage premium and reallocation of tasks from workers to creators is associated with lower employment share of services *ceteris paribus*, which suggests that overall, this channel cannot be the dominant force in accounting for the empirical observations documented in Section 3.

Second, universities are the hubs of technological progress in the local economy. Following Proposition 2 (ii) and (iii), when low-skilled individuals adopt new technology to perform relatively complex tasks, and high-skilled individuals need to perform new tasks developed with

[14] In Appendix A.5 we present analytical results using a simple parametrization of productivity.

innovation, they reallocate tasks previously performed by high-skilled (creators) to low-skilled (workers). Furthermore, this task reallocation increases the share of labor inputs in the service sector, accompanied by a high wage premium and a high price of frontier services, as in Proposition 3 and 4. We also confirm that an innovation of adding new tasks must lead to a larger share of high-skilled workers in the service sector, as in Proposition 5. This is consistent with a significant employment growth of high-skilled services illustrated in Figure 2.

Third, the relative magnitude of task dissemination and invention determines the direction of the wage premium change (Figure 9). Fact 4 in Section 3 highlights that new tasks predominantly emerge in regions with a university. If innovation is sufficiently strong to create enough new tasks, the wage premium for creators will increase, as in Proposition 3. Together, our theory highlights the importance of universities as innovation hubs, which increase both wage premium and employment in services.

4.6 Discussion: Sources of Structural Transformation

To situate the mechanisms in our theory within the broader literature, it is useful to clarify how they relate to, and differ from, existing explanations of structural transformation.

Income effects A key mechanism emphasized in this literature is income effects (e.g., Buera and Kaboski, 2012; Comin, Lashkari, and Mestieri, 2021). In our model, the expenditure share on the service sector is fixed; therefore, there are no income effects. Nonetheless, our model can be easily extended to accommodate non-homothetic preferences. In such an extension, an increase in the wages of creators results in a high expenditure share on the service sector, which in turn drives further demand for tasks that are used for services, which magnifies the mechanisms emphasized in Section 4.4.

Relative price effects Another key mechanism explaining structural transformation is relative price effects: the development of the economy is associated with an increase in the price of services relative to other goods. This effect also exists in our model. As the set of tasks expands, the relative price of new services to goods rises since (i) the relative wage of creators intensively used in new services increases; and (ii) the manufacturing goods price declines as the proportion of workers in production of the manufacturing sector grows. Therefore, we observe such relative price changes along with the structural transformation.

Sectoral productivity In the literature, the relative sectoral productivity growth is often highlighted as a key factor in explaining structural transformation. For example, in Buera et al. (2022), sector-specific productivity growth is an important source of the skill-biased structural change and skill premium. Despite that we abstract from exogenous sectoral productivity, in Appendix A.6, we show that the measure of the endogenous total factor productivity of the manufacturing sector in the model grows if (i) the labor productivity of workers $z^\ell(j)$ increases and the task is allocated more to workers (i.e., an increase in j^*); or (ii) the labor productivity of creators $z^c(j)$ increases and the task is allocated more to creators (i.e., a decrease in j^*). The first case involves the dissemination of tasks, as illustrated in Section 4.3, while the second case relates to the skill-biased technical change, in which education can disproportionately improve the productivity of creators. Taken together, our theory provides a micro-foundation for both (relative) sectoral productivity growth and skill-biased technical change.

5 Quantitative Model

In this section, we extend the model developed previously to quantify the role of universities and to decompose the drivers of local growth of services.[15] We proceed in three steps. First, we present a quantifiable version of our theory in an economy comprising multiple regions and three sectors: manufacturing, low-skilled services, and high-skilled services. Second, we define the general equilibrium and derive an equilibrium relationship that links the growth of services and the wage premium for creators. These equations allow us to isolate the distinct theoretical channels that account for variation in service growth and wage premiums across locations.

The economy consists of N discrete locations; let $\mathcal{R}$ refer to the set of locations. Each location is indexed by subscripts $i, n \in \mathcal{R}$, which corresponds to each CZ in our empirical analysis. There are three sectors indexed by subscripts $k \in \{M, S, H\}$: Manufacturing (M), Low-skilled local services (S) and High-skilled services (H). As in the simple model, there are two types of individuals $\theta \in \{\ell, c\}$: workers (ℓ) and creators (c). The mass of creators in a country is exogenous and given by: $\bar{L}^c = \sum_{i\in\mathcal{R}} L_i^c$. Individuals supply one unit of labor to engage in a task, as described in Section 4. To examine the long-run impact of universities, our baseline specification considers the mobility of creator location decisions.[16]

While the simple theory in Section 4 assumes the range of tasks is exogenous, in this section, we endogenize the creation of new tasks, allowing regions with universities to add new tasks at lower costs. We allow locations to differ in productivity in the manufacturing sector and the productivity of developers in the housing supply.

[15]See Appendix B for the derivation of all theoretical results presented in this section.

[16]In the US, university graduates are more mobile across locations, and the direct effect of their supply on the local labor market is not necessarily large. Instead, these high-skilled individuals tend to gravitate towards locations that offer a wider range of services. Therefore, we introduce mobility of creators in the economy along with different housing prices across locations, which are determined in the local housing market.

5.1 Production Technology

Markets are assumed to be perfectly competitive. Manufacturing firms in location i use the fixed set of tasks $j \in [0, 1]$ to produce manufacturing goods i. Production technology is a CES aggregate of a continuum of tasks with elasticity of substitution σ_M, and the *task-neutral* productivity in the manufacturing sector in location i is A_{iM}. Letting $\gamma_i(j)$ refer cost of task j in location i, profit maximization and zero profits lead to the price of manufacturing goods produced in i:

$$\phi_{iM} = \frac{1}{A_{iM}} \left(\int_0^1 \gamma_i(j)^{1-\sigma_M} dj \right)^{\frac{1}{1-\sigma_M}}. \tag{9}$$

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 a CES aggregate using the set of tasks $j \in [0, I_{\mathbb{S}}]$, and we let σ_S refer to the elasticity of substitution between tasks in low-skilled services. The productivity in the low-skilled services is A_{iS}. The low-skilled services are non-tradable, and the price of low-skilled services (ϕ_{iS}) in location i is:

$$\phi_{iS} = \frac{1}{A_{iS}} \left(\int_0^{I_{\mathbb{S}}} \gamma_i(j)^{1-\sigma_S} dj \right)^{\frac{1}{1-\sigma_S}} \tag{10}$$

For the high-skilled services, firms combine a continuum of tasks $j \in [I_{\mathbb{S}}, J_i]$ under a CES production technology with elasticity of substitution between tasks σ_H. Compared to the low-skilled services, the high-skilled service sector requires relatively higher ordered tasks in production. The price of high-skilled services $(\phi_{i,H})$ in location i is:

$$\phi_{iH} = \frac{1}{A_{iH}} \left(\int_{I_{\mathbb{S}}}^{J_i} \gamma_i(j)^{1-\sigma_H} dj \right)^{\frac{1}{1-\sigma_H}}, \tag{11}$$

where A_{iH} is productivity of high-skilled services. Therefore, the demand for each task $j \in [I_{\mathbb{S}}, J_i]$ is:

$$q_{iH}(j) = \gamma_i(j)^{-\sigma_H} \phi_{iH}^{\sigma_H - 1} A_{iH}^{\sigma_H - 1} E_{iH}, \tag{12}$$

where E_{iH} is expenditure on high-skilled services in location i.

Turning to supply of residential floor spaces, there are competitive developers who supply residential floor spaces (housing) in each location. Residential floor spaces (T_i) in location i is:

$$T_i = G_i(r_i)^{\kappa} \tag{13}$$

where κ is housing supply elasticity and G_i is productivity of developers in location i.

5.2 *Preferences*

We assume a nested preference structure, in which preferences are first defined over housing and consumption across three sectors, and then over manufacturing, low-skilled local services and high-skilled services. In the upper tier of utility, we assume Cobb-Douglas functional form with constant expenditure shares for each type: with $1-\mu^{\theta}$ for housing.[17] For the lower tier of utility, We assume for simplicity a CES functional form over three sectors with elasticity of substitution α. Within the manufacturing sector, we posit a CES functional form over differentiated goods with elasticity of substitution β.

The indirect utility of individuals of type θ in location i becomes:

$$\mathbb{V}_i^{\theta} = \frac{w_i^{\theta} B_i}{\left(\mathbb{P}_i\right)^{\mu^{\theta}} \left(r_i\right)^{1-\mu^{\theta}}}, \quad \theta \in \{\ell, c\}, \tag{14}$$

where w_i^{θ} is wage of type θ in location i; B_i is utility benefit from amenities; r_i is price of residential floor space (rent); and $\mathbb{P}_i$ is price index of consumption across three sectors. Namely, the aggregate price index is:

$$\mathbb{P}_i = \left[\sum_{k \in \{M,S,H\}} \left(\frac{P_{ik}}{\varphi_k}\right)^{1-\alpha}\right]^{\frac{1}{1-\alpha}}, \quad 0 < \alpha < 1 \tag{15}$$

where P_{ik} is price of consumption of sector k in location i; φ_k captures the relative weight of each sector in consumer utility; and α controls the substitutability across sectors. Following the literature of structural transformation in macroeconomics, we assume $0 < \alpha < 1$. Using this, the expenditure share for sector k in location i is:

$$\xi_{ik} = \frac{\left(P_{i,k}/\varphi_k\right)^{1-\alpha}}{\sum_{k' \in \{M,S,H\}} \left(P_{ik}/\varphi_k\right)^{1-\alpha}} \tag{16}$$

Manufacturing goods are differentiated by production place and freely traded across locations within a country. Individuals consume the differentiated manufacturing goods. Therefore the expenditure share of on manufacturing goods produced in i and price index of the manufacturing sector are:

$$\pi_i = \frac{\phi_{iM}^{1-\beta}}{\sum_{n \in \mathcal{R}} \phi_{nM}^{1-\beta}}, \quad P_M = \left(\sum_{n \in \mathcal{R}} \phi_{nM}^{1-\beta}\right)^{\frac{1}{1-\beta}}, \tag{17}$$

respectively. For low-skilled services and high-skilled services, they are non-tradable. Therefore consumption price index for these sectors are given by $P_{iS} = \phi_{iS}$ and $P_{iH} = \phi_{iH}$.

[17] Type-specific expenditure shares on residential floor spaces follow the recent literature on spatial sorting.

There are agglomeration and congestion forces in our model coming from preferences. First, the larger task set lowers the price index of high-skilled services, as a greater variety of differentiated services becomes available. This implies higher real income. Second, consumption of residential floor space creates a dispersion force through floor space prices.

5.3 *Production of tasks*

Each task is produced by workers or creators, as in Section 4. Given the wages of workers (w_i^ℓ) and creators (w_i^c) and their productivity $z^\theta(j)$ for tasks j, cost minimization leads to the cost of each task j in location i satisfying:

$$\gamma_i(j) = \min\left\{\frac{w_i^\ell}{z^\ell(j)},\ \frac{w_i^c}{z^c(j)}\right\} \tag{18}$$

Letting $\omega_i \equiv w_i^\ell / w_i^c$ refer to the wage ratio of workers to creators in location i, the condition (18) holds with equality for the task j^* above which creators perform tasks. Namely, $\omega_i = \frac{z^\ell(j_i^*)}{z^c(j_i^*)}$ for such task j_i^*. The task j_i^* is the highest task performed by workers in location i.

5.4 *Universities and tasks*

We present the determinants of the set of tasks in each location, J_i. Locations differ in η_i, which equals one if location i has a research university and zero otherwise. First, we consider the potential number of new tasks that originate from local universities. Denoting with δ_i the potential number of tasks beyond the task I (i.e., the highest task used in production of low-skilled services) we have:

$$\delta_i = \lambda^{\eta_i}, \tag{19}$$

where λ captures the measure of new tasks when there is a research university $(\eta_i = 1)$ in location i. Research universities are associated with the creation of new tasks, and we assume $\lambda > 1$.

Next, we model the adoption of tasks in the high-skilled service sector. When firms adopt a new task in the production of high-skilled services, they incur a fixed cost, F_i, in terms of capital which we take as a numeraire. The adoption costs depend on a scale parameter in the location (f_i) and the existence of a research university (η_i). When there is a university, the adoption cost becomes low if there is a university. Therefore we suppose that $F_i = \frac{f_i}{1+\eta_i}$.

Firms in the high-skilled services sector adopt task $\widetilde{j}$ in production if the marginal contribution of adopting the task in production exceeds the fixed costs:

$$\frac{\sigma_H}{\sigma_H - 1}\left(\frac{\gamma_i(\widetilde{j})}{P_{iH}}\right)^{1-\sigma_H} E_{iH} \geq \frac{f_i}{1+\eta_i} \tag{20}$$

Since the left-hand side is monotonically decreasing in $\widetilde{j}$, this condition determines the frontier of task adopted by firms $(\widetilde{J}_i)$ in location i. Such task $\widetilde{J}_i$ satisfies (20) with equality.

Together, the set of tasks used in production in location i is determined by $J_i = \min\{I + \delta_i,\ \widetilde{J}_i\}$. Universities affect both the innovation margin (via δ_i) and the adoption margin (via F_i), amplifying the growth of high-skilled services.

5.5 Market Clearing

Creators (c) are freely mobile across locations, while workers (ℓ) are not able to move. Given the indirect utility (14), the free mobility of creators implies that their indirect utility $(\mathbb{V}_i^c)$ is equalized across locations for creators:

$$\mathbb{V}_i^c = \frac{w_i^c B_i}{\left(\mathbb{P}_i\right)^{\mu^c}\left(r_i\right)^{1-\mu^c}} = v^c, \quad \forall\, i = 1, 2, \cdots, N \tag{21}$$

where v^c is the utility level for creators in the economy.[18] Intuitively, housing prices rise in tandem with wage growth and the influx of creators to a location, acting as a dispersion force in the economy.

Goods market clearing conditions for the manufacturing sector imply that demand for manufacturing goods in location i is:

$$E_{iM} = \pi_i \sum_{\theta\in\{\ell,c\}} \sum_{n\in\mathcal{R}} \xi_{nM}\mu^\theta w_n^\theta L_n^\theta \tag{22}$$

For low-skilled and high-skilled services, the market clearing condition requires:

$$\begin{aligned} E_{iS} &= \sum_{\theta\in\{\ell,c\}} \mu^\theta \xi_{iS} w_i^\theta L_i^\theta, \\ E_{iH} &= \sum_{\theta\in\{\ell,c\}} \mu^\theta \xi_{iH} w_i^\theta L_i^\theta, \end{aligned} \tag{23}$$

Labor market clearing condition for workers in each location requires that the total payment for workers $(w_i^\ell L_i^\ell)$ equals the sum of payments to workers in the production of tasks used in manufacturing, low-skilled services and high-skilled services:

$$w_i^\ell L_i^\ell = \int_0^{j_i^*} \frac{\gamma_i(j)^{1-\sigma_M}}{\int_0^1 \gamma_i(j')^{1-\sigma_M} dj'} E_{iM} dj + \int_0^{j_i^*} \frac{\gamma_i(j)^{1-\sigma_S}}{\int_0^{I_{\mathbb{S}}} \gamma_i(j')^{1-\sigma_S} dj'} E_{iS} dj + \int_0^{j_i^*} \frac{\gamma_i(j)^{1-\sigma_H}}{\int_{I_{\mathbb{S}}}^{J_i} \gamma_i(j')^{1-\sigma_H} dj'} E_{iH} dj, \tag{24}$$

Analogously, the labor market clearing condition for creators in location i is:

$$w_i^c L_i^c = \int_{j_i^*}^1 \frac{\gamma_i(j)^{1-\sigma_M}}{\int_0^1 \gamma_i(j')^{1-\sigma_M} dj'} E_{iM} dj + \int_{j_i^*}^{I_{\mathbb{S}}} \frac{\gamma_i(j)^{1-\sigma_S}}{\int_0^{I_{\mathbb{S}}} \gamma_i(j')^{1-\sigma_S} dj'} E_{iS} dj + \int_{j_i^*}^{J_i} \frac{\gamma_i(j)^{1-\sigma_H}}{\int_{I_{\mathbb{S}}}^{J_i} \gamma_i(j')^{1-\sigma_H} dj'} E_{iH} dj, \tag{25}$$

[18] Note that Equation (21) 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 (21) is satisfied for all locations.

where the right-hand side combines the payments to creators performing tasks used in the manufacturing sector (first term), low-skilled services (second term) and high-skilled services (third term).

Lastly, housing market cleaning implies floor space price in location i is given by:

$$r_i = \frac{1}{T_i} \sum_{\theta \in \{\ell, c\}} (1-\mu^\theta) w_i^\theta L_i^\theta \tag{26}$$

5.6 *General Equilibrium*

The equilibrium distribution of economic activities across locations is determined by (i) the set of parameters in preference and technology (α, μ^θ, φ_k, β, σ_k); (ii) the task performance of creators and workers in the aggregate economy $z^\theta(j)$; and (iii) the heterogeneity across locations in the mass of workers $\{L_i^\ell\}$, universities $\{\eta_i\}$, task-neutral productivity $\{A_{ik}\}$, productivity of developers $\{G_i\}$, amenities $\{B_i\}$, fixed cost in creating new tasks $\{f_i\}$ and total number of creators in the country $(\bar{L}^c)$. We now define the equilibrium for this multi-region economy.

Definition 2. *Given the exogenous variables of the model and economy-wide parameters, the equilibrium is characterized by the following endogenous variables: wages of workers and creators $\{w_i^\theta\}$, the distribution of creators $\{L_i^c\}$, the task assignment $\{j_i^*\}$, the frontier of tasks $\{J_i\}$, floor space prices $\{r_i\}$ and common real income (v^c) such that (i) task assigned workers and creators to minimize the cost* (18)*; (ii) goods and labor market clear* (22)–(25)*; (iii) firms adopt tasks satisfying* (20)*; (iv) profit maximization and zero profits of developers and housing market clear* (26)*; and (v) free mobility condition for creators* (21).

We present the details of equilibrium conditions and how to solve them in Appendix B.2. We use the quantitative model to evaluate the implication of the existence of universities in the local economy in the spatial distribution of creators (high-skilled labor) and employment of services through a number of different channels.

Let us consider a location with highly ranked universities, where the university parameter (η_i) is large. Suppose there is a positive shock on innovation of new tasks (λ). First, a location with a university can expand the task set, which lowers the price index of high-skilled services, as a greater variety of differentiated services becomes available. Second, creation of new tasks raises the relative wage of creators compared to workers $(1/\omega_i)$ as shown in Proposition 2. Combined with the lower price index of services, this leads to an increase in the real income of creators $(\mathbb{V}_i^c)$, attracting more creators from other locations.

Third, inflow of creators increases the employment share of the service sector, since creators tend to produce tasks that are intensively used in high-skilled services. Moreover, the production of such services requires a broad array of tasks, thereby increasing the share of both workers and creators engaged in service-related activities. As discussed in Section 4.4, these dynamics disproportionately raise the labor share in services. Fourth, a larger number of creators (L_i^c) leads to higher floor space prices. Therefore, this process continues until the housing price (r_i) reaches a sufficient high, leading to the dispersion of creators to different locations.

These mechanisms are at work for other types of positive shocks, including a shock to the productivity of the manufacturing sector. In a nutshell, differences in the level of universities across locations lead to different spatial patterns of wage premium and structural transformation, taking labor away from manufacturing to services due to a *positive feedback loop* between task creation and rising demand for high-skilled services and creators. We quantitatively evaluate the importance of this channel in the next section.

6 Quantification

6.1 Model Parameters

Table 2 summarizes the economy-wide parameters and assigned values in our calibration.

Table 2: Parameter values and sources

Parameter	Notation	Value	Source
Elasticity of substitution between tasks			
— in manufacturing	σ_M	3	Note $\sigma_k > 1$
— in low-skilled services	σ_S	3	
— in high-skilled services	σ_H	3	
Expenditure share on residential floor space			
— of high-skilled labor	μ^c	0.15	Diamond and Moretti (2024)
— of low-skilled workers	μ^ℓ	0.25	Diamond and Moretti (2024)
Elasticity of substitution across sectors	α	0.2	Comin, Lashkari, and Mestieri (2021)
Floor space supply elasticity	κ	1.75	Saiz (2010)
Elasticity of substitution between manufacturing goods	β	4	Trade literature

Note: This table summarizes the parameter values in the model. The first column lists each parameter; the second column contains the corresponding notation; the third column gives its calibrated value; and the fourth column summarizes the source for the calibrated value.

We also posit the following parameterization of productivity in performing tasks:

$$\begin{aligned} z_t^\ell(j) &= \Omega_t^\ell e^{-\delta j}, \\ z_t^c(j) &= \Omega_t^c e^{-\varepsilon j} \end{aligned} \quad \varepsilon < \delta, \tag{27}$$

where the scale parameters $(\Omega_t^\ell, \Omega_t^c)$ capture absolute advantage in performing tasks for different types of workers; and the shape parameters (δ, ε) capture the comparative advantage of them.

6.2 *Estimation of Task Performance*

We use the two periods, 1980 (denoted by period 0) and 2015 (denoted by period 1), to estimate the key parameters in (27): $(\varepsilon,\ \delta,\ \Omega_0^c,\ \Omega_0^\ell,\ \Omega_1^c,\ \Omega_1^\ell)$ based on the observation of wages of different types of workers $(w_{i,0}^c, w_{i,0}^\ell, w_{i,1}^c, w_{i,1}^\ell)$ and employment distribution $(L_{iM,0}^c, L_{iM,0}^\ell, L_{iM,1}^c, L_{iM,1}^\ell)$ in manufacturing sector. First, we have a equilibrium relationship:

$$\frac{L_{iM,t}^c}{L_{iM,t}^\ell}\left(\frac{w_{i,t}^c}{w_{i,t}^\ell}\right)^{\sigma_M} = \frac{\delta}{\varepsilon}\left(\frac{\Omega_t^c}{\Omega_t^\ell}\right)^{\sigma_M-1}\frac{e^{-\varepsilon(\sigma_M-1)j_{i,t}^*}-e^{-\varepsilon(\sigma_M-1)}}{1-e^{-\delta(\sigma_M-1)j_{i,t}^*}} \tag{28}$$

for each period. In addition, manufacturing goods market clearing condition and zero profit conditions implies:

$$\ln(w_{i,t}^c L_{iM,t}^c + w_{i,t}^\ell L_{iM,t}^\ell) - \frac{1}{N}\sum_{n\in\mathcal{R}}\ln(w_{n,t}^c L_{nM,t}^c + w_{n,t}^\ell L_{nM,t}^\ell) = -(1-\beta)\ln\bar{A}_{iM,t}$$
$$+(1-\beta)\left[F(w_{i,t}^c, w_{i,t}^\ell, j_{i,t}^* : \Omega_t^c, \Omega_t^\ell, \varepsilon, \delta, \sigma_M) - \frac{1}{N}\sum_{n\in\mathcal{R}}\ln F(w_{n,t}^c, w_{n,t}^\ell, j_{n,t}^* : \Omega_t^c, \Omega_t^\ell, \varepsilon, \delta, \sigma_M)\right] \tag{29}$$

where $\ln\bar{A}_{iM,t} = \ln A_{iM,t} - \frac{1}{N}\sum_{n\in\mathcal{R}}\ln A_{nM,t}$ captures the deviation of sectoral productivity in location i from its average; and $F(w_{i,t}^c, w_{i,t}^\ell, j_{i,t}^* : \Omega_t^c, \Omega_t^\ell, \varepsilon, \delta)$ captures the cost of tasks used in manufacturing sector:

$$F(w_{i,t}^c, w_{i,t}^\ell, j_{i,t}^* : \Omega_t^c, \Omega_t^\ell, \varepsilon, \delta) = \left[\left(\frac{w_{i,t}^c}{\Omega_t^c}\right)^{1-\sigma_M}\frac{e^{-\varepsilon(\sigma_M-1)j_{i,t}^*}-e^{-\varepsilon(\sigma_M-1)}}{\varepsilon(\sigma_M-1)} + \left(\frac{w_{i,t}^\ell}{\Omega_t^\ell}\right)^{1-\sigma_M}\frac{1-e^{-\delta(\sigma_M-1)j_{i,t}^*}}{\delta(\sigma_M-1)}\right]^{\frac{1}{1-\sigma_M}} \tag{30}$$

We solve (29) for $\ln\bar{A}_{iM,t}$ for each period and taking the difference between the two periods yields:

$$\Delta\ln\bar{A}_{iM} = \ln\bar{A}_{iM,1} - \ln\bar{A}_{iM,0} \tag{31}$$

Then, we impose a moment condition that $\mathbb{E}\big[I_i\cdot\Delta\ln\bar{A}_{iM}\big] = 0$, where instruments I_i include the initial manufacturing share and initial size of total employment.

6.3 *Model Inversion*

We next use the observed data and the structure of our model to recover unobserved variables, such as sectoral level productivity, prices, amenities and frontier tasks, which are inputs into our counterfactuals below. We explain the model inversion in order. We present the details are in Appendix C.

First, we exploit market clearing conditions (22) and (23) to obtain sectoral prices. Conditional on the data on wages $\{w_{i,t}^\theta\}$, employment $\{L_{ik,t}^\theta\}$ and parameters $(\sigma_M, \mu^\theta, \alpha)$, we solve $N\times 3$

equations (22) and (23) together for productivity of manufacturing sector, price of manufacturing goods, price of low-skilled services, and price of high-skilled services adjusted with taste parameters $(\varphi_{k,t})$. Using the prices, we obtain the aggregate price index in each location (15) for each period.

Second, we solve the labor market clearing condition for low-skilled services conditional on the observed wages and employment and inverted prices and task threshold to obtain productivity of low-skilled services adjusted with taste parameter across locations. Analogously, we solve the labor market clearing condition for high-skilled services for the adjusted productivity of high-skilled services and the index of highest task in each location $(J_{i,t})$ conditional on the number of college and non-college graduates in high-skilled service sector and their wages across locations.

Third, we use the free mobility condition for college graduates (21) to pin down the locational amenities. Given the wages of college graduates, average rent, and inverted price index across locations, we solve the free mobility conditions for amenities for college graduate. We also use the floor space market clearing condition (26) to compute the location advantage of developers conditional on the data on wage, employment and average rent.

Fourth, the equilibrium condition (20) for the adoption of the frontier task (J_i) satisfies:

$$\frac{\sigma_H}{\sigma_H - 1}\left(w^c_{i,t}\right)^{1-\sigma_H} z^c(J_{i,t})^{\sigma_H-1}\left(\widetilde{P}_{iH,t}\right)^{\sigma_H-1}\left(\widetilde{A}_{iH,t}\right)^{\sigma_H-1} E_{iH,t} = F_{i,t}, \tag{32}$$

where, on the left-hand side, $w^c_{i,t}$ is wage of college graduates; $\widetilde{P}_{iH,t}$ is adjusted price of high-skilled services; $\widetilde{A}_{iH,t}$ is adjusted productivity of high-skilled services; and $E_{iH,t}$ is employment of high-skilled services. Conditional on the data and inverted fundamentals, we obtain a location advantage in new task adoption, $F_{i,t}$.

6.4 Task Frontier

We show the calibration results here (TBA).

7 Accounting for Growth of Services and Wage Premium in US

With these estimates, we are ready to conduct counterfactual analysis to quantify the degree to which universities drive local structural transformation as well as the underlying mechanisms. In our first exercise, we feed in the average $(L^c_{i,2015}, J_{i,2015})$ across regions with universities to each region j without one, with other fundamentals in j being their current values. We then solve the counterfactual $(w^c_j, w^n_j, E_{iM}, E_{iS}, E_{iH})$ for 2015. The same procedure is repeated for all j's.

In the second counterfactual exercise, we examine the three channels through which universities contribute to local structural transformation: (i) supply of high-skilled labor, (ii) creation of new tasks, and (iii) the migration of high-skilled labor. Given the distribution of universities, we fix the high-skilled-to-low-skilled ratio in 2015 to their 1980 levels for regions with universities, to quantify (i). Similarly, we restrict the set of tasks (indexed by J_i) in 2015 to their 1980 levels for regions with universities, in order to quantify (ii). Lastly, we consider an economy with the same set of fundamentals but no migration to quantify (iii).

8 Conclusion

Structural transformation in the US economy exhibited an uneven pattern across regions. This paper studies how universities have contributed to the rise of services to explain such variation. We find four novel empirical facts using rich datasets on local labor markets and universities. First, CZs with universities, particularly high-ranked ones, experienced a greater increase in service sector employment and establishments. Second, regional differences in structural transformation are largely explained by structural changes within tasks and skills. Third, CZs with universities have consistently exhibited higher skill premiums for college-educated workers over the past four decades. Finally, new tasks tend to emerge disproportionately in regions with universities.

Motivated by these patterns, we develop a new theory of local structural transformation featuring heterogeneous task distributions across sectors, endogenous skill-task matching, and an endogenous skill premium. In this framework, universities serve a dual role in the local labor market: they supply high-skilled labor and generate new tasks through innovation. Both functions contribute to the transition from manufacturing to services, but they have distinct implications for task allocation and wage outcomes, which allows us to distinguish the relative importance of each role. Our model highlights that the innovation role of universities is particularly critical in jointly explaining the stronger growth of the service sector and the rising skill premium observed in university regions.

Our work contributes to a deeper understanding of the mechanisms behind regional economic divergence in the US. In ongoing research, we aim to quantify the contribution of universities to local structural transformation, with implications for place-based policy, higher education investment, and regional development strategies.

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