

# Skilled Tradable Services: The Transformation of U.S. High-Skill Labor Markets\*

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## Abstract

We study a group of service industries that are skill-intensive, widely traded, and have recently seen explosive wage growth. Between 1980 and 2015, these “Skilled Tradable Services” accounted for a sharply increasing share of employment among the highest earning Americans. Unlike any other sector, their wage growth was strongly biased toward the densest local labor markets and the highest paying firms. These services alone explain 30% of the increase in inequality between the 50th and 90th percentiles of the wage distribution. We offer an explanation for these patterns that highlights the complementarity between the non-rivalry of knowledge and changes in communication costs.

*Keywords:* Wage Inequality, Skill Biased, Technological Change, Urban Growth, Trade and Geography

*JEL Codes:* J31, O33, R11, R12

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# 1. INTRODUCTION

The nature of high-skill wage growth has changed in recent decades. Wages for high-skill workers have grown rapidly and, at the same time, have stopped converging across local labor markets in the United States. The former has led to substantial increases in overall wage inequality, the latter to the increasing concentration of high-skill workers in a small number of “superstar” cities. These developments have coincided with a host of economic and political challenges. House prices in large local labor markets have reached record highs, rural areas are struggling to attract high-skill workers, and the political rift between these regions continues to deepen.

We argue that a group of service industries that are highly skill-intensive and widely traded internationally is key to understanding these changes. These “Skilled Tradable Services” comprise industries such as management consulting, finance, information sectors, and the management of companies. We show that Skilled Tradable Services play a prominent role in the rise of income inequality and the spatial divergence of high-skill wages in the United States. Despite this, the sector has attracted surprisingly little attention in the literature.<sup>1</sup>

We begin by documenting a series of facts that suggest that Skilled Tradable Services (STS) play a prominent role in the rise of income inequality and the spatial divergence of high-skill wages in the U.S. over the past four decades. STS industries have two features in common that have interacted with recent technological change to produce these developments. First, their primary input is knowledge, and this knowledge is used principally to codify and solve problems. However, while knowledge is fundamentally non-rival, sharing it is not free: communication frictions limit the ability of knowledge workers to exploit the non-rivalry of their knowledge. In recent decades, a series of innovations has drastically reduced the cost of supplying knowledge at a distance for these services (see Corrado and Hulten (2010), Fort (2017), and Eckert (2018)). As in Rosen (1981), declines in these costs amplify small differences in productivity into large differences in wage growth. The superstar logic in Rosen (1981) can explain why the most skilled workers have seen such rapid wage growth; it can also explain why being in the most productive regions is central to their success.

The Yale College graduating class of 2017 is a prime example of the importance of STS among high-skill workers. Almost 54% of the class moved to one of just five “superstar” cities: New York, Boston, San Francisco, Washington D.C., and Los Angeles. These labor markets account for only 14% of total U.S. employment. Once there, 70% began working in STS. Overall, more than 59% of all Yale

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<sup>1</sup>Jensen et al. (2005) is an early paper documenting the rise of tradable services and the growth in international service trade. Eckert (2018) is the first paper to relate the growth of Skilled Tradable Services to recent trends of high-skill wage growth across U.S. labor markets. He argues that Skilled Tradable Service industries have become substantially more tradable as part of the information technology revolution of the last four decades and that has generated high-skill labor demand in locations historically most specialized in business services such as New York, San Francisco, and Washington D.C.

graduates in 2017 started their careers in STS. In contrast, the nationwide STS employment share is only 20%, hinting at the sector's central role in explaining skilled wage growth in the United States.<sup>2</sup>

We begin by documenting four facts that together describe the remarkable rise of STS in recent decades. They highlight that the patterns of growth observed for STS are unlike those of any other sector during this period.

First, since 1980, the STS sector has seen faster wage growth than all other sectors in the U.S. economy. However, employment growth has been much slower than for most other service industries.

Second, STS industries now account for a large part of employment in the upper percentiles of the U.S. wage distribution. In 1980 employment shares in STS services ranged from 10% in the lowest decile of the wage distribution to about 20% among workers in the top decile. By 2010, employment shares among the lowest wage earners had fallen slightly but risen to more than 40% in the top decile. Together with the previous fact, this suggests that STS industries are central to understanding the dilation of the wage distribution between 1980 and 2010.

Third, STS wage growth has been fastest in the densest metropolitan areas, something not true for any other sector. However, these areas did not increase their share in national STS employment.

Fourth, the establishment-level wage distribution in STS has dilated, with faster wage growth at higher-paying establishments. This is not true in other sectors, suggesting that STS establishments are an important driver behind the increase in between-firm inequality (see Song et al. (2018)). At the same time, average employment has not changed differentially across the establishment-level wage distribution.

These facts taken together suggest that recent technological change has led to superstar wage growth dynamics in STS. While talent is one source of being a superstar, working in the most productive region and at the most productive firms is also important. Payroll has been reallocated to the most productive workers, labor markets, and firms, while employment - consistent with superstar theories of wage growth - has not.<sup>3</sup>

To formalize this, we propose a simple model of knowledge work, in which communication frictions limit the ability of workers to exploit the non-rivalry of their knowledge. In this environment, we show that a secular decline in communication costs generates the empirical patterns we have uncovered in the data. The most productive, high-skill workers begin sharing their knowledge across space and experience outsized wage growth as a result. Our model builds on seminal work by Garicano (2000) and Garicano and Rossi-Hansberg (2006). In their framework, production occurs by solving problems of varying difficulty. More skilled workers can solve a larger set of problems. When

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<sup>2</sup>These statistics are obtained from Yale University's Office of Career Strategy 2017 First Destination Survey conducted among all graduating students from Yale College. Details are provided in Appendix A.

<sup>3</sup>Koenig (2019) contrasts the wage and employment implications of the Rosen (1981) superstar wage growth mechanism with those of an aggregate skill-biased demand shift.

communication costs are low enough, the most skilled workers can specialize in the most difficult problems in the economy. As communication costs fall further, the most skilled workers can aggregate more and more of those difficult problems and see their wages rise rapidly as a result. Relative to Garicano and Rossi-Hansberg (2006), we introduce regions into the analysis and highlight the differences between communication costs across and within locations.

The model highlights that labor markets with a comparative advantage in producing STS prior to changes in communication costs should benefit most from their reduction. We test this model prediction formally by relating local STS wage growth to two proxy measures for local comparative advantage in STS industries. In models of interregional trade, the local employment share in a traded industry serves as a revealed measure of comparative advantage. Additionally, work by Davis and Dingel (2019) and others suggest that population density or population size of a location creates communication advantages for high-skill activities. We show that both measures in 1980 strongly predict the subsequent growth in the ratio of STS relative to other sectors' wages between 1980-2010 on the local labor market level.

We conclude by quantifying the contribution of STS to the rapid wage growth in “superstar” cities, and the overall increase in income inequality.<sup>4</sup> We demonstrate that the strong spatial bias in STS wage growth explains the entirety of the faster wage growth in the densest local labor markets. We also show that STS wage growth accounts for approximately 30% of the overall increase in the 90/50 ratio in the wage distribution.<sup>5</sup>

In conclusion, we argue that the increase in wage inequality, the recent economic success of high-skill workers, and the large wage gains of the densest metropolitan areas cannot be understood without the STS sector.

## 2. DATA SOURCES AND MEASUREMENT

We document our facts throughout the largest and most-used sources of U.S. employment data. We summarize our data construction and measurement in this section. We use the restricted-use Longitudinal Business Database and the public-use U.S. Decennial Census data to document our four facts in the main body of the paper. In addition, we assert the robustness of our findings in the public-use Quarterly Census of Employment and Wages. Appendix A contains additional information on data sources and data processing.

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<sup>4</sup>We define the densest cities accounting for 30% of U.S. employment as superstar cities for measurement. The set comprises New York, Boston, San Francisco, Washington D.C., and Los Angeles, which are often regarded as superstar cities in the popular press.

<sup>5</sup>See, e.g., Katz (1999) and Autor et al. (2008), for a discussion of the dilation of the U.S. wage distribution in recent decades.

## 2.1 Longitudinal Business Database

The Longitudinal Business Database (LBD) is an administrative restricted-use data set made available by the U.S. Census Bureau and based on the Census' Business Register derived from Internal Revenue Service tax data. The database covers large portions of private non-farm employment and selected public-sector activity, between 1975 and today.<sup>6</sup> The files contain longitudinally linked data for all U.S. establishments with one or more paid employees. For each establishment information on parent firms, industry, detailed location, total annual payroll, and total employment count is available. We use the industry concordances provided by Fort and Klimek (2016) to reclassify all data on a consistent NAICS 2012 industry basis from 1980 to 2016. We compute the establishment-level average by dividing the total payroll by total employment in each year. We follow Autor and Dorn (2013) in defining local labor markets based on the concept of commuting zones developed by Tolbert and Sizer (1996), who used county-level commuting data from the 1990 Census to create 741 clusters of counties that exhibit large commuting flows within and weak ones across their boundaries. The union of all commuting zones covers the entire United States. For the rest of the paper, our spatial unit of analysis is these commuting zones, which, at times, we also refer to as local labor markets.

## 2.2 U.S. Decennial Census Data

The United States Decennial Census is a constitutionally mandated nationally representative survey conducted every 10 years. We use the Census Integrated Public Use Micro Samples for the years 1980, 1990, and 2000, and the American Community Survey (ACS) for 2010 (Ruggles et al. (2015)). The Census samples for 1980, 1990, 2000, and 2010 include 5% of the U.S. population. There are two important issues with the Census data. First, contrary to the administrative records in the LBD, in the Decennial Census respondents *self-report*. Second, income data are top-coded, whereby the highest incomes are censored in the public-use data. This will likely further attenuate our results (Burkhauser et al., 2012). Both issues are important in reconciling findings across the data sets we use.

We follow Autor and Dorn (2013) in our sample selection procedure. Our sample consists of individuals who were between age 16 and 64 and who worked in the year preceding the survey. Our main measure of annual wages is each respondent's total pre-tax wage and salary income - that is, money received as an employee - for the previous year. Sources of income in the data include wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. Payments-in-kind or reimbursements for business expenses are not included. We constructed a crosswalk to

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<sup>6</sup>The LBD does not cover Agriculture, Forestry and Fishing (SIC Division A), railroads (SIC 40), U.S. Postal Service (SIC 43), Certificated Passenger Air Carriers (part of SIC 4512), Elementary and Secondary Schools (SIC 821), Colleges and Universities (SIC 822), Labor Organizations (SIC 863), Political Organizations (SIC 865), Religious Organizations (SIC 866) and Public Administration (SIC Division J) (see Jarmin and Miranda (2002) for details).

map the industry identifiers in the data to a consistent NAICS 2012 basis throughout the decades. All calculations are weighted by the Census sampling weight. We assign workers into one of four educational categories: high school or less, some college, college, more than college. With the help of the crosswalk provided by Autor and Dorn (2013), we map the geographic identifiers in the data to the commuting zones (CZs) developed by Tolbert and Sizer (1996).

## 2.3 Other Data Sources

We draw on two other sources of data. To define Skilled Tradable Services, we use the Input-Output (IO) tables in producer prices provided by the Bureau of Economic Analysis (BEA). For robustness, we also document most of the facts derived from the LBD in another source of administrative data, the Quarterly Census of Employment and Wages (QCEW). The QCEW contains comprehensive employment and payroll data for U.S. establishments by industry and location and is published by the Bureau of Labor Statistics. Different from the LBD, the QCEW is derived from records of the state and federal unemployment insurance programs. A notable limitation of the QCEW data is that they are only available on a NAICS 2012 basis from 1990 onward, restricting our comparison to that period.

## 3. DEFINING SKILLED TRADABLE SERVICES (STS)

As outlined in the introduction, the defining features of the Skilled Tradable Services (STS) sector are that its industries are “knowledge-intensive” and increasingly traded domestically and abroad. As simple proxies for these two characteristics, we construct measures of skill intensity and international trade volume for each of the 14 2-digit NAICS service industries in the U.S. economy.

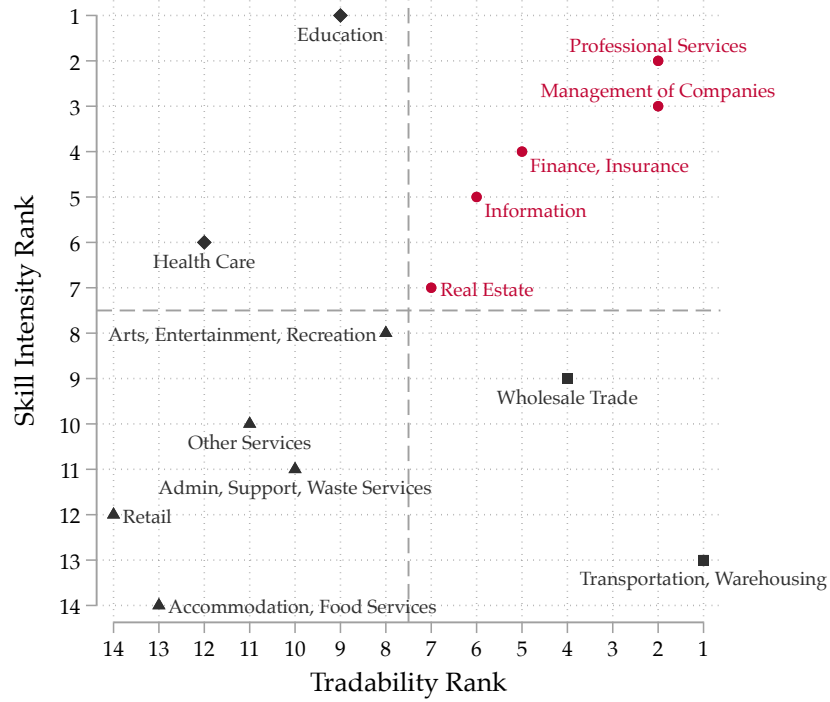
As a proxy measure for knowledge intensity, we compute the fraction of workers with at least a college degree in the 2010 public-use U.S. Decennial Census micro-data (available via Ruggles et al. (2015)) for each 2-digit NAICS service industry. We then assign a rank to each service industry with the most skill-intensive ranked first.

We measure the tradability of a sector by looking at its international trade volumes. Using international trade data from the Bureau of Economic Analysis (BEA) Input-Output tables in 2010, we compute the sum of imports and exports over total U.S. absorption for each NAICS-2 service industry. We call this number the “tradability” score. We rank industries by their tradability score with the highest scoring industry ranked first.<sup>7</sup>

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<sup>7</sup>As other papers have noted, the trade data for services are likely subject to substantial measurement error. The most pertinent case is that of NAICS-55, “Management of Companies.” U.S. companies engage in foreign direct investment (see, e.g., Burstein and Monge-Naranjo (2009)), sending knowledge and management capabilities abroad in large quantities *especially within* multinational corporations. Such intra-firm “shipments” are largely unmeasured by the BEA and NAICS-55 exports appear minuscule. To correct for this, we assign the tradability score of the NAICS-54 sector “Professional Services” to the NAICS-55 sector “Management of Companies.”

FIGURE 1: DEFINING SKILLED TRADABLE SERVICES

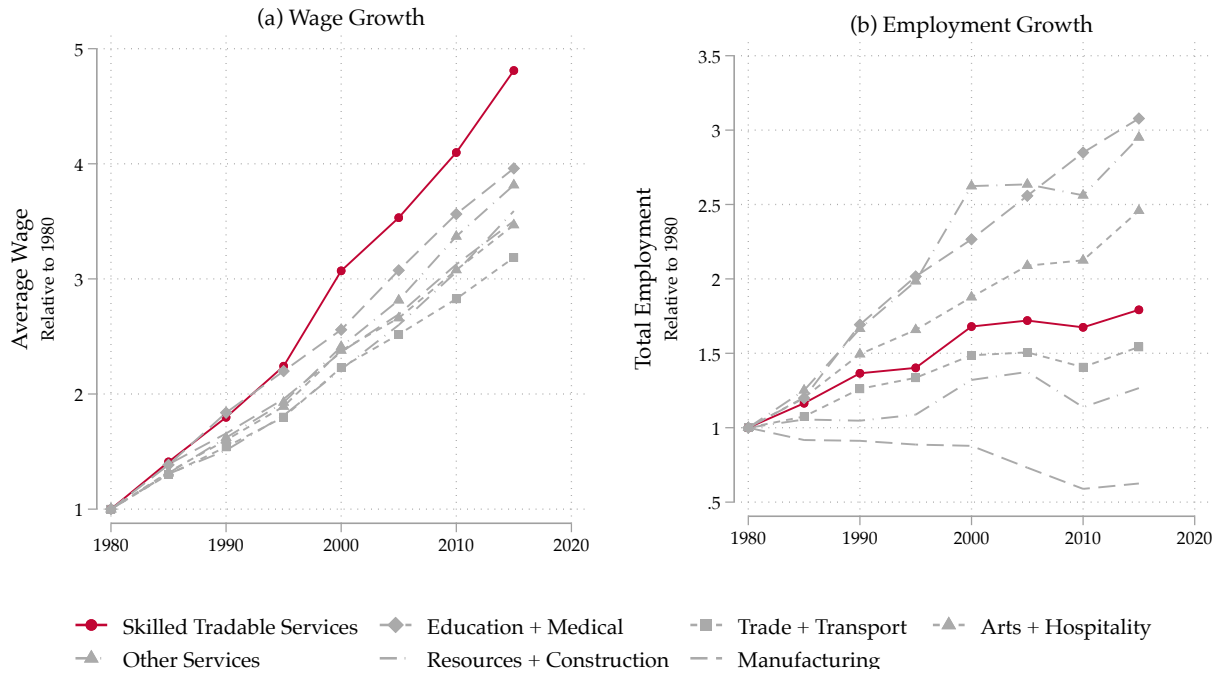


*Notes:* To construct the figure we use micro-data from the American Community Survey for 2010, made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. We map the Census' industry identifiers to 2-digit NAICS codes. Skill intensity is computed as the fraction of college-educated workers in a sector. We construct a tradability measure by computing (Exports+Import)/Output for every 2-digit NAICS service industry using the 2012 BEA Input-Output tables. We assign "Management of Companies" the tradability score of "Professional Services." We additionally adjust the Education sector using the Census of Local Government to account for non-private-sector production.

We define Skilled Tradable Services as those five industries that are both more skilled and more tradable than at least half of the other 2-digit NAICS service industries. Figure 1 graphs the tradability rank of all NAICS-2 service industries against their skill-intensity rank. The figure also shows the three other types of service industries: low-skill tradable, high-skill non-tradable, and low-skill non-tradable. Throughout the paper, we highlight differences between the Skilled Tradable Services sector and high-skill non-tradable service industries such as education and medical services. While both groups are skill intensive, they appear to interact very differently with recent technological change, suggesting a complementarity between the tradability and skill intensity of a sector. This complementarity is the focus of our paper.

For much of the rest of the paper, we refer to Skilled Tradable Services as STS. We group non-STS service industries into four groups: Trade and Transport (Transportation and Warehousing, Retail Trade, Wholesale Trade), Education and Medical (Educational Services, Healthcare and Social Assistance), Arts and Hospitality (Arts, Entertainment, and Recreation, Accommodation and Food Services), Other Services (Admin, Support, and Waste Services, Other Services). For comparison, we

FIGURE 2: WAGE AND EMPLOYMENT GROWTH BY SECTOR



*Notes:* The left panel shows the average nominal wages by sector relative to 1980. The right panel shows employment by sector relative to 1980. The data underlying this figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). Average wages at the sectoral level are computed by aggregating payroll and employment over all establishments within each sectoral grouping and year, and then dividing the former by the latter. The wage measure is normalized within sector by dividing by the average sectoral wage in 1980. Employment is calculated by aggregating the employment of all establishments with each sector, and then normalized within sector by dividing by total employment in 1980.

also add non-service-sector aggregates to some figures: Resources and Construction (Agriculture, Mining, Utilities, Construction) and Manufacturing.

## 4. THE RISE OF SKILLED TRADABLE SERVICES

In this section, we present a set of facts about the rise of the Skilled Tradable Services sector since 1980.

**Fact 1.** *After 1980, STS wage growth outpaced all other sectors. Employment growth was moderate.*

Figure 2 shows average sectoral wages relative to their 1980 level for all sectors. Both the STS sector and the education and medical sector have seen faster wage growth than the remaining sectors in the economy. However, in the mid-1990s wage growth in the STS sector accelerated. In 2017, average wages in the STS sector had grown five-fold since 1980, while other sectors had increased their wages by only 3.5 times on average.<sup>8</sup>

<sup>8</sup>Figures A.1 and A.2 in the Appendix show that Figure 2 looks similar when constructed with the QCEW or the Population Census data.



FIGURE 3: SKILLED TRADABLE SERVICES (STS) EMPLOYMENT SHARES  
ACROSS THE WAGE DISTRIBUTION



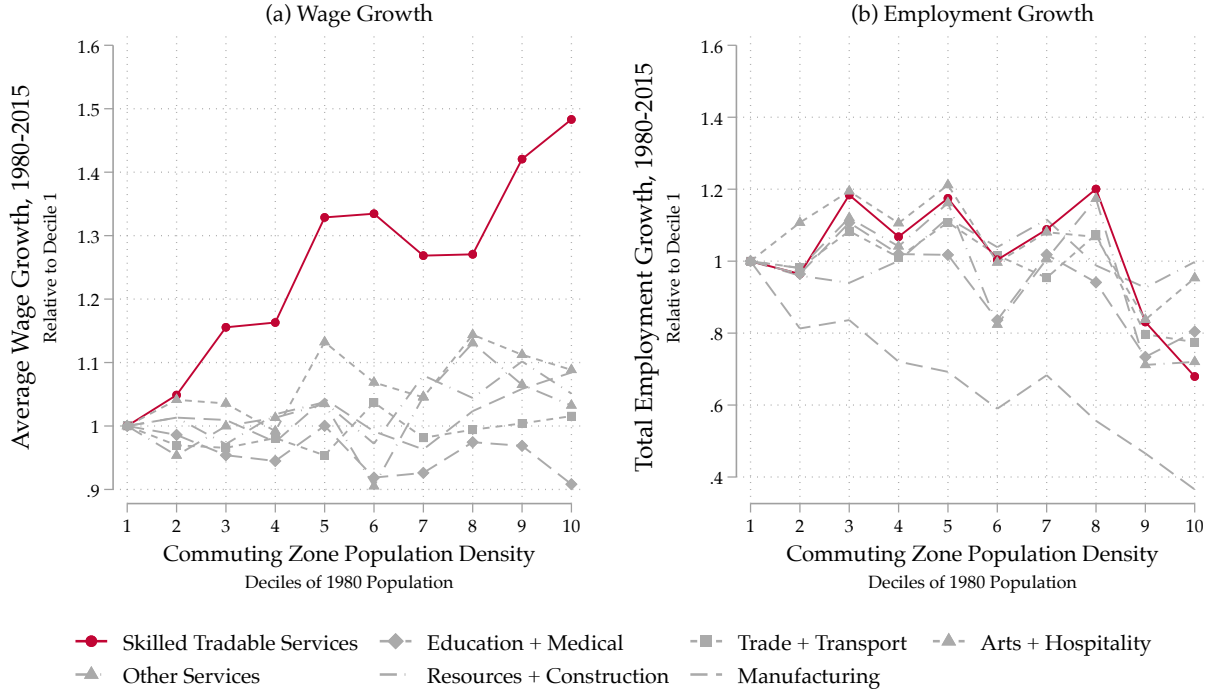
*Notes:* This figure shows the fraction of workers within each percentile of the annual wage distribution who work in the Skilled Tradable Services sector. To construct the figure we use Decennial Census micro-data for 1980, 1990, and 2000, and micro-data from the American Community Survey for 2010, all made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We use the Census sample weights to construct the income distribution. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define the Skilled Tradable Services sector.

Figure A.3 in the Appendix replicates Figure 2 for all 2-digit NAICS service industries shown in Figure 1. STS industries exhibit faster wage growth than all other service industries in the U.S. economy. Notably, other high-skill-intensive sectors, such as the medical sector, see much slower wage growth. These differences between sectors suggest that skill intensity alone is not sufficient to explain why STS wage growth is outpacing the rest of the economy.

Figure 2b reveals that STS employment growth has not kept pace with STS wage growth. While wages grew fastest in the STS industries, employment did not. Abstracting from the trade and transport sector, the STS industries experienced the slowest employment growth of the entire service sector.<sup>9</sup> In contrast to the STS, the education and medical sector also displays the fastest employment growth, matching its fast wage growth seen in Figure 2a.

<sup>9</sup>Figures A.1 and A.2 in the Appendix show that these employment trends are not unique to the LBD, but hold in all our data sets.

FIGURE 4: WAGE AND EMPLOYMENT GROWTH BY SECTOR AND COMMUTING ZONE POPULATION DENSITY



*Notes:* The left panel shows the growth in average wages by sector and commuting zone density between 1980 and 2015. The right panel does the same for employment growth. The data underlying this figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). 1980 population figures are taken from the Decennial Census and commuting zone boundaries are from Tolbert and Sizer (1996). Commuting zone deciles are constructed by ordering all commuting zones (cf. Section 2) by their population density in 1980 and then forming deciles of increasing density, each containing commuting zones that jointly account for 10% of the national population in 1980. Decile 1 contains the least dense commuting zones, decile 10 the densest commuting zones. Average wages at the sectoral and commuting zone decile level are computed by aggregating payroll over all establishments within each sectoral grouping, commuting zone decile and year, and dividing by total employment in that group in that year. Growth is calculated as the percentage change in these measures between 1980 and 2015. Last, we normalize the growth rates relative to the first commuting zone decile within each sectoral group. We assign each establishment in the LBD a commuting zone density decile via the zip code in which each establishment is located.

Together, the two panels of Figure 2 suggest that the nature of STS wage growth is different than that of the Education and Medical sector. Holding other job attributes constant, outsized wage growth should attract skilled workers from other sectors. However, employment growth has been fastest *outside* STS. In this paper, we argue that the crucial difference between the STS sector and the Education and Medical sector is that STS industries produce a tradable output.<sup>10</sup>

**Fact 2.** *In 2010, most top earners worked in STS. In 1980 they did not.*

Figure 3 shows STS employment shares across the percentiles of the U.S. wage distribution and across time. For each percentile of the wage distribution in each year, we compute the fraction of workers

<sup>10</sup>Figure A.14 shows the left panel of Figure 2 side by side with an alternative version with wages deflated using the consumer price index. With real wages, the growth difference between STS and the rest of the economy appears even more pronounced.

employed in STS. The construction of the figure requires individual micro-data for which we use the Decennial Census and American Community Survey data described above.

The employment share in STS industries increased considerably among the highest income percentiles in the U.S. economy between 1980 and 2010. Among workers in the 99th percentile of the U.S. income distribution, the employment share went from 27% in 1980 to 55% in 2010. The median of the wage distribution constitutes an inflection point for employment share growth: above it STS employment shares have grown, below it, they have decreased. Figure 2 showed that these developments aggregate to only a moderate overall increase in STS employment.

Figure A.6 in the Appendix shows the share of workers in various education groups within a sector's total employment relative to the employment shares of these education groups in the national economy. The college share among those employed in STS has increased even relative to the overall college share of employment in the U.S. economy. At the same time, the less-than-college share of employment in STS has fallen faster than the respective employment share in the overall U.S. economy. No other 1-digit sector in the U.S. economy exhibits this polarizing pattern, as the remaining panels of Figure A.6 demonstrate.

However, fast STS wage growth is not just a result of compositional changes. The left panel of Figure A.7 in the Appendix demonstrates that also *within* each educational group (high school, some college, college, college plus), the STS sector exhibits the fastest wage growth among all sectors.

In combination with Fact 1, Figure 3 and Figure A.7 suggest that while STS employment has not grown much overall, the composition of its labor force has changed substantially. Today workers in STS are on average much higher up in the U.S. wage distribution and much more educated than the average worker, and much more so than in 1980.

**Fact 3.** *Since 1980, STS wages have grown fastest in the densest labor markets, without these markets' share in national STS employment increasing.*

Next, we introduce one of the most striking features of STS wage growth: its spatial bias. We order the 741 commuting zones in the United States by their population density in 1980.<sup>11</sup> Then we group commuting zones together starting with the least dense into ten groups that each account for 10% of U.S. employment in 1980. The first group contains many small commuting zones; the last three very large ones: Chicago, New York, and Newark.

Figure 4a shows average wage growth by sector across the commuting zones within each of these ten bins. Wage growth in STS industries exhibits a striking gradient across labor markets ordered by

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<sup>11</sup>See Tolbert and Sizer (1996) for their construction and Autor and Dorn (2013) for their introduction into economics. These 741 commuting zones cover the entire territory of the United States.

density. STS wages grew considerably faster in the densest U.S. labor markets. Wage growth in no other sector exhibited these patterns.<sup>12</sup>

Figure 5 focuses on wage growth across sectors within the least and most dense commuting zone deciles. It reveals differences between high-skill industries that are tradable and those that are not, according to our ranking in Figure 1. The non-tradable but skill-intensive Education and Medical sector has seen similar wage growth within the least and most dense deciles of employment. In contrast, the tradable and high-skill STS industries have grown much faster than the Education and Medical sector in the densest commuting zones, and much slower in the least dense ones. The figure also suggests that without STS, the least and most dense labor markets would have seen very similar overall wage growth.

Figure A.8 in the Appendix shows wage growth by education group across the density-ranked commuting zones. The more educated the individuals, the more their wage growth is biased toward denser regions. Comparing A.8 and the left panel of 4 also shows that the STS wage growth gradient across commuting zones ordered by density is much steeper than it is for any individual education group.

Turning to employment, 4b reveals that the densest commuting zones have not increased their share in national STS employment since 1980. All sectors, with the exception of manufacturing, have seen relatively balanced employment share growth across our commuting zone ordering. Not only did STS not see outsized employment growth at the national level, but across commuting zones, there is no reallocation of employment toward places with the largest wage gains.

In Figure A.9 in the Appendix, we look at the reallocation of employment and payroll across commuting zones more formally. For each commuting zone, we compute the ratio of its share in national payroll of a sector relative to its share in the national employment of that sector. Figure A.9 presents the growth in this measure between 1980 and 2015 for each commuting zone decile and sector. It shows that the densest commuting zones have increased their share of payroll much faster than their share of employment in STS industries.

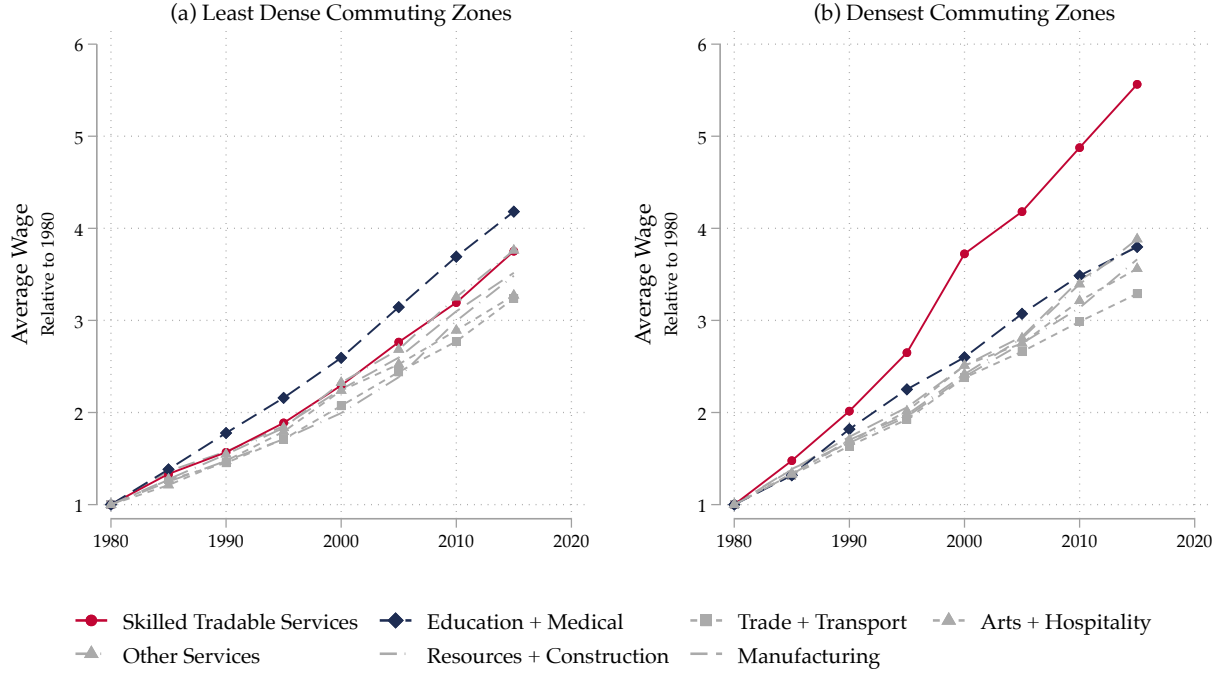
**Fact 4.** *Since 1980, wages have grown fastest for the highest paying STS establishments, without increases in average employment.*

We calculate average wages at every U.S. establishment for every year between 1980 and 2015. For each year, we then order establishments by their average wage within two groups: the STS sector, and all other sectors. Among the so ordered establishments, we form deciles each decile containing 10% of the establishments within that sector. Lastly, we compute the growth rate of the average

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<sup>12</sup>The left panel of Figure A.4 in the Appendix replicates the left panel of Figure 4 using the Population Census and shows that the general picture is the same across data sets. The right panel of Figure A.4 also shows that trends look very similar with hourly instead of annual wages.

FIGURE 5: WAGE GROWTH IN LOWEST AND HIGHEST DENSITY COMMUTING ZONES BY SECTOR



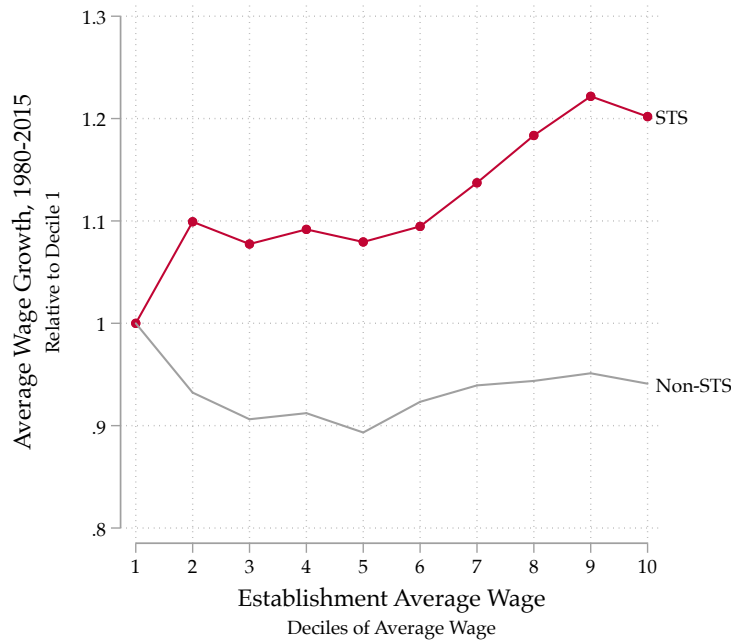
*Notes:* The left panel shows the growth in average wages between 1980 and 2015 for establishments located in the least dense decile of commuting zone population. The right panel does the same for the densest commuting zone. The data underlying this figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). 1980 population figures are taken from the Decennial Census and commuting zone boundaries are from Tolbert and Sizer (1996). Commuting zone deciles are constructed by ordering all commuting zones (cf. Section 2) by their population density in 1980 and then forming deciles of increasing density each containing commuting zones that jointly account for 10% of the national population in 1980. Decile 1 contains the least dense commuting zones, decile 10 the densest commuting zones. Average wages at the sectoral and commuting zone decile level are computed via aggregating payroll over all establishments within each sectoral grouping, commuting zone decile and year, and dividing by total employment in that group in that year. These are then normalized within sector by dividing by the average sectoral wage in 1980 for establishments located in the least dense decile of commuting zone population. We assign each establishment in the LBD a commuting zone density decile via the zip code in which each establishment is located.

wage across these deciles between 1980 to 2015. Over the years, the identity of establishments within each decile changed, but each decile's size remained constant. In this setting, we study how relative average wages among establishments have developed.

Figure 6 shows the growth in the average establishment-level wage across the deciles, with wage growth normalized to 1 in the first decile for each sector. STS wages at the highest paying establishments have increased more than at the lowest paying ones. As a result, overall inequality between STS establishments in average wages has increased substantially since 1980, mirroring findings of rising between-firm wage inequality in Song et al. (2018). In contrast, in non-STS industries, average wages in establishments in all deciles have grown at roughly the same rate (the first decile is an exception).

In summary, part of the fast aggregate wage growth in STS wages (cf. Figure 2) reflects the fact that

FIGURE 6: WAGE GROWTH FOR SKILLED TRADABLE SERVICES (STS)  
AND THE REST OF THE ECONOMY (Non-STs) BY ESTABLISHMENT AVERAGE WAGE



*Notes:* The figure shows average wage growth between 1980 and 2015 within deciles of establishment-level average wage for the Skilled Tradable Services sector (STS) and the rest of the economy (non-STs). We normalize wage growth by the lowest establishment average wage decile. The data underlying this figure comes from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). In each year, we rank all establishments by their average wage and then construct deciles that each account for 10% of establishments. Average wages within deciles and year are computed by aggregating payroll over all establishments within each decile and year, and dividing by total employment in that group in that year. Growth is calculated as the percentage change in these measures between 1980 and 2015. Last, we normalize the growth rates relative to the first establishment average wage decile.

today, the highest paying STS establishments pay more relative to the median STS establishments than in 1980. Figure A.13 in the Appendix reveals that a similar pattern does not hold for average establishment size. In the STS sector, the highest paying establishments were, on average smaller in 2015 than in 1980, while the least paying ones have maintained a constant average size. The contrast between wage and employment growth is reminiscent of Figure 4, which showed the densest labor markets’ rapid STS wage but moderate employment growth. Figures A.13 and 4 suggest that the highest paying STS establishments are located in the densest labor markets and have experienced rapid wage growth without increasing their overall employment.

Taken together, Facts 1 to 4 suggest a “superstar” dynamic for STS industries operating across workers, firms, and commuting zones. In the following section, we provide a stylized explanation for these empirical patterns that formalizes the superstar intuition.

## 5. A MODEL OF KNOWLEDGE WORK AND COMMUNICATION COSTS

The seminal work by Rosen (1981) formalized the idea that declines in communication costs would lead to the creation of “superstars” in professions in which special talent (e.g., specific knowledge) is important. For example, the advent of television raised the wages of the best comedians in the United States, and lowered earnings for less funny individuals (see Koenig (2019)). At the heart of this mechanism is a market size effect: declining communication costs allow the most talented or knowledgeable individuals to serve a larger share of the market with their superior skills. Kaplan and Rauh (2013) argue that similar market size effects can explain a large part of the rise in top incomes and overall income inequality in the 1980s.

This superstar mechanism is appealing in explaining our facts. STS industries are knowledge-intensive and the information technology revolution is likely to have made them more tradable, allowing the best STS workers and firms to increase their market share. What we add to the theory is the role of space. As Figure A.9 in the Appendix highlights, a superstar effect seems to also hold across regions: the densest regions managed to substantially increase their share in the national STS payroll relative to their share in national STS employment. Through the superstar framework two explanations are possible: either these regions are inherently more productive in producing STS services, or they are home to the most talented STS workers for some reason. In reality, both things are likely true. Regardless of the channel, regions appear to be central in understanding the changes in the STS industries and, with it, changes in the return to skill, rises in inequality, and regional disparities. We build on the framework by Garicano and Rossi-Hansberg (2006) to illustrate the simple idea that non-rival assets of an individual, such as talent, are magnified through falling communication costs across regions.

### 5.1 Theory

We propose a stylized explanation for the growth of Skilled Tradable Services in the United States. The key insight is that declining communication costs *across regions* – i.e., “trade costs” of STS services – amplify the non-rivalry of knowledge work. We extend work by Garicano and Rossi-Hansberg (2006), which provides an elegant framework for thinking about the role of communication costs in structuring the organization of production between knowledge and physical labor.

#### 5.1.1 Environment

Production requires two inputs: labor and knowledge. Agents are indexed by their skill type  $s$ , associated with a problem-solving ability  $q_s \in [0, 1]$ . To produce one unit of output, workers must solve a randomly drawn problem from the interval  $[0, 1]$ . An agent of type  $s$ , can solve any problem

indexed between 0 and  $q_s$ . “Drawing” problems has a time cost: each agent draws one problem per unit of time. Once a problem is encountered, *solving* a problem costs no time if the worker possesses the knowledge to address it. In expectation, an agent of type  $s$  can solve the problem she encounters with probability  $q_s$  and hence produce an expected output of  $q_s$  per unit of time.

There are two types of agents: low-skill agents ( $s = l$ ) and high-skill agents ( $s = h$ ) that differ in their problem-solving ability, i.e.,  $q_l < q_h$ . The expected output of these workers, when working by themselves, is hence  $q_l$  or  $q_h$ , respectively.

Instead of originating and solving problems themselves, workers can specialize in the problems that are too hard for other workers to solve. In expectation, a low-skill worker is unable to solve  $1 - q_L$  of the problems he encounters. If in lieu of giving up on these problems, she can communicate them to a more skilled worker who may possess the knowledge to solve them.<sup>13</sup> Recall that what takes time is to draw a problem, but not to solve it. A problem can be *transferred*, i.e., *communicated*, to a high-skill worker who can solve it at no additional cost if he has the knowledge to do so. Two caveats apply: First, communication is costly: it takes  $h$  units of time to communicate a problem to a manager, and the manager bears this cost alone. Second, if a low-skill worker cannot solve a problem he cannot determine whether the high-skill worker will be able to either, i.e., low-skill workers cannot just communicate problems they know high-skill workers can solve. This pins down the number of low-skill workers that a high-skill manager can help solve their unresolved problems,  $n$ , in a unit of time:

$$n(1 - q_L)h = 1. \quad (1)$$

The expected output produced per unit of time by  $n$  low-skill workers paired with a high-skill manager is  $y = nq_H$ . We think of workers who specialize in solving difficult problems as managers, management consultants, or computer programmers, i.e., skilled tradable service workers. We show in Appendix B that it is never optimal for low-skill workers to become managers, or for high-skill workers to manage other high-skill workers.

The amount of time it takes to communicate a problem from a worker to a manager,  $h$ , can be thought of as indexing (the limits to) the non-rivalry of knowledge. As  $h \rightarrow 0$ , a single manager is sufficient to solve the excess problems of all workers in the economy. The insight here, already present in Garicano (2000), is that while knowledge is non-rival in theory, sharing knowledge is costly, making it somewhat rival in practice.

### 5.1.2 Communication Across and Within Regions

So far the environment is identical to Garicano and Rossi-Hansberg (2006). We depart from their setup by introducing regions and a distinction between communication costs *across* versus *within*

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<sup>13</sup>In particular, problems in the range  $[q_l, q_h]$  can be solved by high-skill and not low-skill workers.



them.<sup>14</sup>

For simplicity, suppose there are two regions, and communication of problems across these regions takes  $\tilde{h}$  units of time, where  $\tilde{h} = h\tau$  with  $\tau > 1$ , while communication within remains possible at cost  $h$ . It is easier to communicate problems when worker and manager are in the same location, i.e.,  $h < \tilde{h}$ . So communication makes it difficult for managers to deploy their non-rival problem-solving ability across regions.

We index regions by  $c$  and call them the *dense location* ( $c = D$ ) and *sparse location* ( $c = S$ ). The dense location has a fundamental advantage in communication, i.e.,  $h^D < h^S$ : communicating problems is easier when workers are more tightly packed.

There is a mass  $M_H$  of high-skill workers and a mass  $M_L$  of low-skill workers in the economy. The utility of an individual of type  $s$  from locating in location  $c$  is

$$U_s^c = w_s^c (m_s^c)^{-\eta},$$

where  $m_s^c$  is the mass of type  $s$  agents in location  $c$  and  $w_s^c$  is the type  $s$  wage rate in location  $c$ .<sup>15</sup>

### 5.1.3 Solving the Model

We solve the model twice: first for prohibitively high cross-regional communication costs, i.e.,  $\tau$  large; Then for moderate levels of  $\tau$  for which problems are traded across regions. We think of these two cases as prior to and after the information technology revolution that started in the 1980s (see, e.g., Corrado and Hulten (2010)).

For parsimony, we make two stylized assumptions on model parameters. We assume that communication *within* the sparse location is prohibitively costly, i.e.,  $h_S$  is sufficiently large. We also suppose low-skill workers cannot move across regions, so that their mass in each region,  $m_L^c$ , is a parameter of the model.

**Case 1: Prohibitive Interregional Communication Costs** Since communication is prohibitively costly in the sparse city, both low- and high-skill workers originate their own problems and produce an output of  $q_s$  in expectation. As a result, wages are given by  $w_H^S = q_H$  and  $w_L^S = q_L$  for high- and low-skill workers, respectively.

In the dense city, however, specializing in knowledge work can be profitable. Adapting equation 1 to the regional model shows that a high-skill worker specializing in knowledge work can advise a

<sup>14</sup>Santamaria (2019) also introduces space into the Garicano and Rossi-Hansberg (2006) model; however, she does not allow for communication of problems across regional boundaries.

<sup>15</sup>The formulation captures, in reduced form, an elastic housing supply with segregated housing markets for high- and low-income earners.

number

$$n^D = \frac{1}{(1 - q_L)h^D} \quad (2)$$

of low-skill workers per unit of time. Recall that the expected output of such a team in a unit of time is  $y = n^D q_H$ : work is split in a way that of every unit mass of problems originated by low-skill workers, they solve  $[0, q_L]$  while the high-skill workers solve  $[q_L, q_H]$ . The return to a manager from specializing in knowledge work is hence:

$$w_H^D = n^D(q_H - w_L^D), \quad (3)$$

i.e., she is the residual claimant on the output of the team.

When teams are formed in a location, the relative abundance of high- to low-skill workers determines relative wages. We assume that parameters are such that high-skill workers are relatively abundant in the dense city. As a result, low-skill workers capture the surplus of team formation and high-skill workers in the dense city compete to form teams until they all earn  $w_H^D = q_H$ , regardless of whether they lead teams or produce for themselves. Using this alongside equation 3, we obtain an expression for the low-skill wage:

$$w_L^D = \frac{n^D q_H - q_H}{n^D} = q_H(1 - (1 - q_L)h^D), \quad (4)$$

where the second equality follows from plugging in the optimal team size from equation 2. Teams form as long as  $w_L^D \geq q_L$ , which holds as long as  $h^D$  is not too large.

High-skill workers earn  $w_c^D = q_H$  in both locations. Spatial equilibrium dictates that indirect utilities for high-skill workers need to equalize across regions. Given equilibrium wages, there must be an equal number of them in both dense and sparse locations, i.e.,

$$m_H^D = m_H^S.$$

For this equilibrium to prevail, high-skill workers need to be sufficiently abundant in the dense city. We derive the cutoff for  $m_L^D$  – a parameter – in Appendix B.<sup>16</sup>

**Case 2: Low Interregional Communication Costs** We now consider the case with low communication costs. First, note that since  $h_S$  is prohibitively high, managers in the sparse location cannot help solve the problems of agents located elsewhere. Managers in the dense location, however, do find it profitable to apply their knowledge to problems generated in the sparse city. The size of such a

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<sup>16</sup>The following parameter condition needs to hold:  $m_L^D < \frac{M_H}{2}(1 - q_L)h^D$ .

cross-region team with the manager headquartered in the dense location is:

$$n_{CR}^D = \frac{1}{(1 - q_L)\tilde{h}^D} = \frac{1}{(1 - q_L)h^D\tau}, \quad (5)$$

where the subscript indicates the cross-regional nature of the team. Equation 5 demonstrates that if communication across regions is costly ( $\tau \rightarrow \infty$ ), cross-regional teams do not form. Equations 2 and 5 together show that cross-regional teams are smaller than local teams, reflecting the higher communication costs across space. In Appendix B, we show that there is a  $\bar{\tau}$  such that for all  $\tau > \bar{\tau}$  cross-regional teams would be too small to be economically viable for high-skill workers to manage.

With some restrictions on relative quantities of high- to low-skill workers (see Appendix B), high-skill workers in the dense location now capture the surplus from forming cross-regional teams. As a result, their wage is now given by:

$$w_H^D = n_{CR}^D(q_H - q_L) = \frac{(q_H - q_L)}{(1 - q_L)h^D\tau}. \quad (6)$$

The expression in equation 6 reflects the fact that low-skill workers in the sparse location are abundant, with an outside option of earning  $q_L$  by working for themselves. Intuitively, once high-skill workers can ship their knowledge across regions, knowledge becomes the scarce factor in the dense location and high-skill workers earn increasing rents. With this as the skill wage, the low-skill wage in the dense location is given by:

$$w_L^D = \frac{n^D q_H - w_H^D}{n^D} = \frac{n^D q_H - \frac{(q_H - q_L)}{(1 - q_L)h^D\tau}}{n^D}$$

Spatial equilibrium for high-skill workers requires

$$\frac{q_H}{(1 - m_H^D)^\eta} = \frac{q_H - q_L}{(1 - q_L)h^D\tau(m_H^D)^\eta}$$

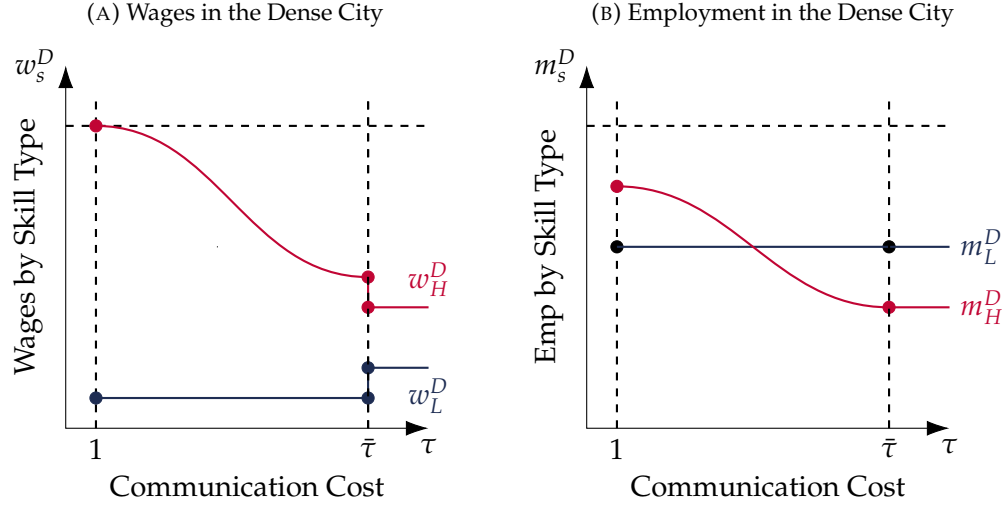
which can be explicitly solved for  $m_H^D$  as a function of parameters.

In Appendix B, we show the restrictions on parameters for the equilibrium of the economy to behave as outlined above.

#### 5.1.4 Comparative Statics

The left panel of Figure 7 shows the dense location to small location high-skill wage ratio as a function of  $\tau$ . The right panel shows the ratio of high- to low-skill workers in the dense location as a function of  $\tau$ .

FIGURE 7: COMPARATIVE STATICS IN THE MODEL



*Notes:* The figure shows wages by skill group within the dense region in the left panel and employment by skill group in the dense region in the right panel, in both cases as a function of the interregional communication cost parameter  $\tau$ . When  $\tau > \bar{\tau}$ , changes in  $\tau$  have no effect on wages or quantities, since forming teams across regions is prohibitively expensive. When  $\tau < \bar{\tau}$ , declines in  $\tau$  raise wages for high-skill workers in the dense region as they benefit from the ability to form increasingly large interregional teams. High-skill workers' wages jump up and low-skill workers' wages jump down at  $\tau = \bar{\tau}$ , as the high-skill workers' outside option increases and improves their bargaining situation with the (scarce) low-skill workers in the dense city. Increasing wages for high-skill workers in the dense location that serves as the only location from which such teams can be formed draws more high-skill workers into the city; low-skill workers cannot move by assumption.

The model connects with the preceding facts in a stylized way. We interpret high-skill workers specializing in knowledge work as STS workers.

As interregional communication costs fall, STS wages outgrow those of other types of work and workers in the economy. In fact, the real wages of low-skill workers fall on average, while the wages of high-skill workers in non-STs industries remain constant. At the same time aggregate employment in STS increases.

Second, the STS employment share among high-skill workers increases. Since they earned more than low-skill workers initially, this translates into an increase in the STS employment share on the right tale of the income distribution, mirroring the fact presented in Figure 3.

Third, STS wages grow in the dense location even as high-skill workers move in. At the same time real wages for low-skill workers decrease in the dense city. Importantly, the model also predicts that STS employment and wages rise in locations that initially specialize in STS work. In Section 6, we test this prediction more formally.

The model does not pin down firm boundaries. Managers could be viewed as external management consultants that aggregate the problems of individual low-skill workers in the economy and who each run one-man firms. Alternatively, we could think of low-skill workers forming teams of size

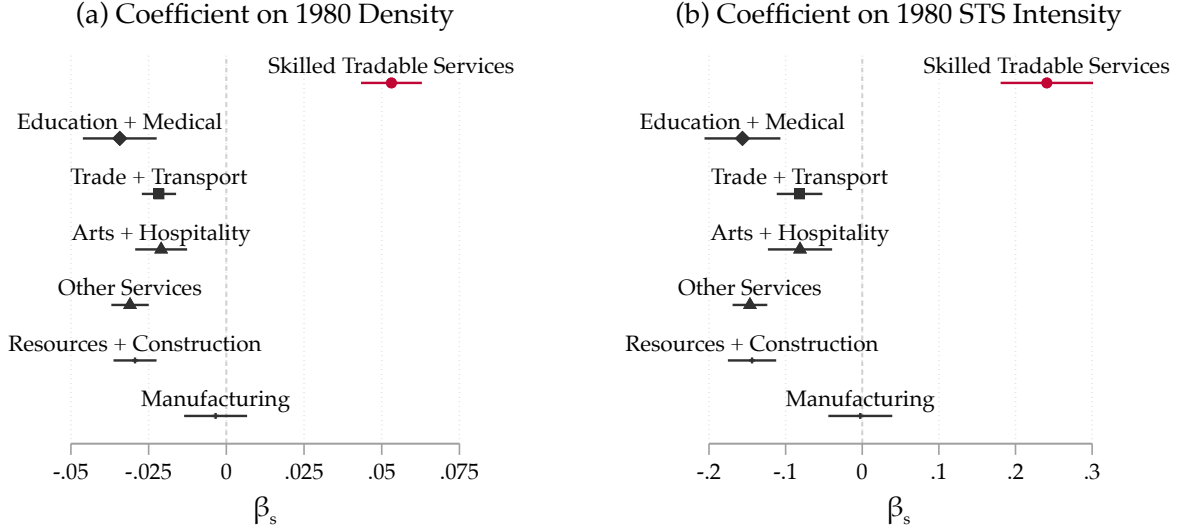
$n + 1$  with a high-skill manager. As a result, the model does not directly speak to our last fact. The working paper version of Garicano (2000) shows how to solve for prices and wages in a decentralized version of the model in which individuals trade problems they cannot solve in a “market for knowledge.”

While our model is stylized, it can explain many features of the data as a function of an aggregate shock - the decline in communication costs - that is itself not spatially biased in nature. The model highlights the interaction between skills that are non-rival in nature with the decline in communication costs, which allows their “scaling” across regions.

While it would be beyond the scope of this paper to provide direct evidence on the decline in communication costs, Eckert (2018) provides both direct and indirect evidence that trade costs for high-skill services and communication cost indices have declined since the 1980s.

Lastly, we want to highlight that, similar to Eckert (2018), declines in communication costs raise the aggregate skill premium, i.e., the aggregate average earnings of high- relative to low-skill workers in the economy. In other words, declines in communication costs are a form of skill-biased technological change because of the interaction of knowledge-intensive non-rival skills and communication. We believe that the facts presented in this paper highlight that explanations of the rise in the skilled wage premium in the United States since the 1980s cannot ignore the spatial bias in skilled wage growth we document.

FIGURE 8: REGRESSION OF COMMUTING ZONE WAGE PREMIUM CHANGE ON INITIAL COMPARATIVE ADVANTAGE BY SECTOR



*Notes:* This figure graphically shows results for  $\beta_s$  from Equation 7. These coefficients represent the interaction of a sectoral dummy with two measures of STS comparative advantage. The left panel measures comparative advantage using the 1980 density of a commuting zone. The right panel measures comparative advantage using the 1980 STS employment share of a commuting zone. Robust standard errors with 1980 population weights. Confidence intervals are computed at the 95% two-sided level. Full regression results available in the online appendix. To construct the figure we use Decennial Census micro-data for 1980, and micro-data from the American Community Survey for 2010, made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We use the Census sample weights to construct the income distribution. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define the Skilled Tradable Services sector.

## 6. REVEALED COMPARATIVE ADVANTAGE AND SKILLED TRADABLE SERVICES WAGE GROWTH

The model highlights that labor markets with a comparative advantage in producing Skilled Tradable Services should see the largest wage gains following a reduction in communication costs. The idea that declines in trade frictions disproportionately raise demand for the sector in which a given region has a comparative advantage goes back to Stolper and Samuelson (1941).<sup>17</sup> The strong bias of STS wage growth toward denser regions (see Figure 4) provides suggestive evidence in favor of a trade explanation for the aggregate STS wage growth over the latest decades.

We test the Stolper and Samuelson-like (1941) prediction of our theory formally by considering two measures of local comparative advantage in STS services. First, we construct STS employment shares for each commuting zone in 1980, which classical models of international trade suggest as a revealed measure of comparative advantage for traded sectors. Work by Davis and Dingel (2019) and others further suggests that population density creates communication advantages for high-skill activities

<sup>17</sup>Eckert (2018) also applies the theorem in the context of Skilled Tradable Services trade across U.S. local labor markets.

and hence generates a comparative advantage for STS in dense regions. We use the population density of commuting zones in 1980 as an alternative proxy measure for its comparative advantage in STS industries pre-communication cost decline.

Using these two measures of comparative advantage, we run two commuting-zone-level regressions. We estimate specifications of the form:

$$\Delta_{2015,1980}y_{c,s} = \alpha_s + \beta_s x_{c,1980} + \epsilon_{c,s}. \quad (7)$$

The subscript  $c$  indexes commuting zones and  $s$  indexes sectors. The operator  $\Delta_{2015,1980}$  denotes 35-year changes in the outcome variable  $y_{c,s}$  and  $x_{c,1980}$  is a measure of initial comparative advantage.

We consider the within-commuting-zone wage premium in sector  $s$  as outcome variable  $y_{c,s}$ , which we compute as the leave-one-out average:

$$\text{wage premium}_{c,s} = \frac{\text{payroll}_{c,s}}{\text{employment}_{c,s}} / \frac{\sum_{s' \neq s} \text{payroll}_{c,s'}}{\sum_{s' \neq s} \text{employment}_{c,s'}}, \quad (8)$$

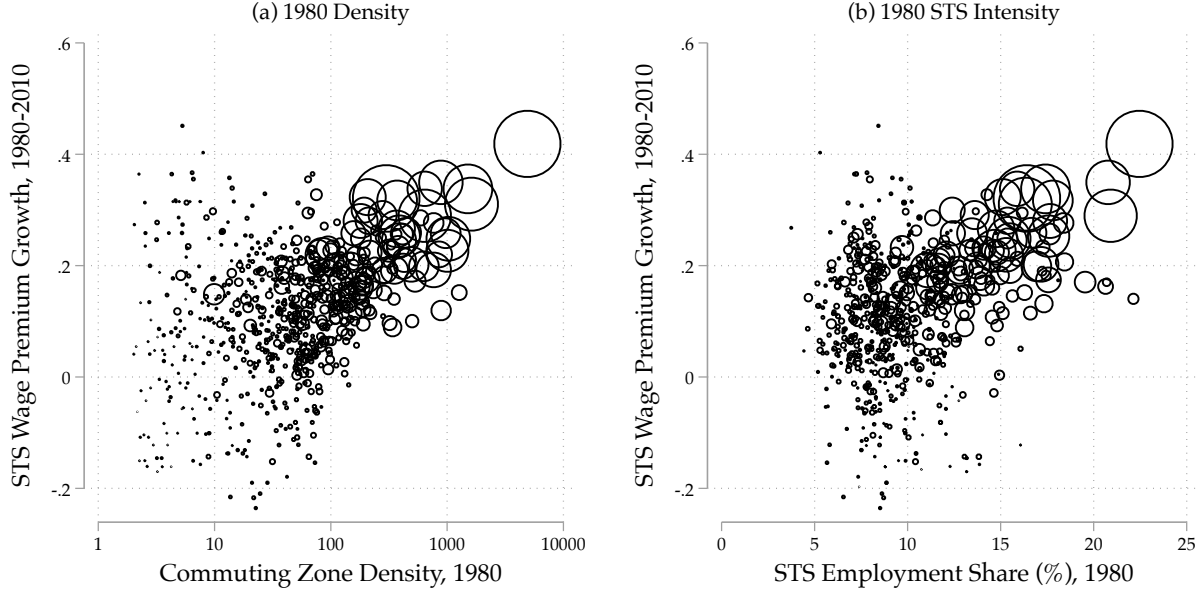
which is the average wage in sector  $s$  in commuting zone  $c$ , relative to the average wage in all other sectors in commuting zone  $c$ .

Figure 8 shows the regression results for  $\beta_s$  for both measures of initial comparative advantage. The coefficient  $\beta_s$  characterizes the relative growth of the wage premium within a sector as a function of the initial comparative advantage of a particular commuting zone. A positive number indicates that wages grew faster in regions with an initial comparative advantage in the STS sector. Both initial STS employment share and initial population density are strong predictors for the subsequent growth of the STS wage premium. Doubling the initial density of a commuting zone corresponds to an increase in the growth in STS wage premium of 5%. In the Education and Medical sector, the change in the wage premium is 2.5% less when a commuting zone is twice as dense.

Figure 9 shows changes in the within-commuting-zone wage premium for the STS sector as a function of our two measures of commuting zone comparative advantage. Both panels show an increasing relationship between the initial comparative advantage in STS and subsequent growth in the STS wage premium.

In the Appendix, Figures A.10 and A.11 replicate Figures 8 and 9 with the outcome variable  $y_{c,s}$  simply the sector  $s$  wage in commuting zone  $c$ . These figures show very similar patterns to the figures in this section.

FIGURE 9: CHANGE IN COMMUTING ZONE SKILLED TRADABLE SERVICES (STS) WAGE PREMIUM BY INITIAL COMPARATIVE ADVANTAGE



*Notes:* This figure shows changes in the within commuting-zone wage premium from 1980-2015 as a function of pre-existing indicators of STS comparative advantage. The left panel uses the 1980 population density as a measure of STS comparative advantage. The right panel uses the 1980 STS employment share as a measure of STS comparative advantage. The size of the circles indicates the 1980 population of the commuting zones. Within-commuting-zone STS wage premiums computed using Equation 8. To construct the figure we use Decennial Census micro-data for 1980, and micro-data from the American Community Survey for 2010, made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We use the Census sample weights to construct the income distribution. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define the Skilled Tradable Services sector.

## 7. SKILLED TRADABLE SERVICES, SUPERSTAR CITIES, AND WAGE INEQUALITY

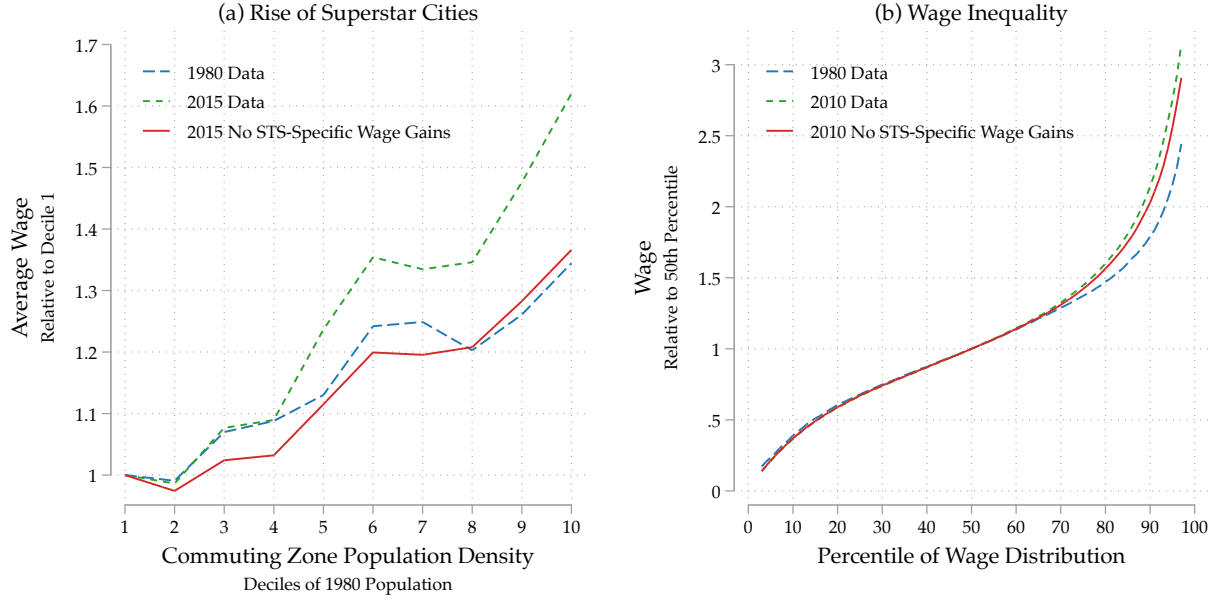
We conclude by quantifying the contribution of STS wage and employment growth to the rapid wage growth in “superstar” cities, and the overall increase in income inequality using simple statistical decompositions. For the sake of measurement, we define the densest cities accounting for 30% of U.S. employment as superstar cities. This set comprises New York, Boston, San Francisco, Washington D.C., and Los Angeles, often regarded as “superstar” cities in the popular press.

### 7.1 The Rise of Superstar Cities

Figure 10 reveals that the wage gap between the densest and least dense commuting zones has increased substantially since 1980. In 1980, a worker in the top density decile made 35% more than a worker in the bottom decile. Today, a similar worker earns 60% more. Figure 4 in Section 4 showed



FIGURE 10: SKILLED TRADABLE SERVICES (STS), THE RISE OF SUPERSTAR CITIES,  
AND THE INCREASE IN WAGE INEQUALITY



*Notes:* The left panel shows that the wage-density gradient has increased substantially since 1980. The solid red line shows what the density wage premium would be without STS wage growth. The right panel shows the increase in inequality (relative to the 50th percentile of the wage distribution) from 1980 to 2010. The solid red line shows the wage distribution if STS-wage gains mirrored all other sectors. The data underlying the left panel come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). 1980 population figures are taken from the Decennial Census and commuting zone boundaries are from Tolbert and Sizer (1996). Commuting zone deciles are constructed by ordering all commuting zones (cf. Section 2) by their population density in 1980 and then forming deciles of increasing density, each containing commuting zones that jointly account for 10% of the national population in 1980. Average wages at the sectoral and commuting zone decile level are computed by aggregating payroll over all establishments within each sectoral grouping, commuting zone decile and year, and dividing by total employment in that group in that year. Last, we normalize the wage rates relative to the first commuting zone decile within each sectoral group. To construct the right panel, we use Decennial Census micro-data for 1980, and micro-data from the American Community Survey for 2010, made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We use the Census sample weights to construct the income distribution. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define the Skilled Tradable Services sector.

that STS are the only set of industries whose wage growth between 1980 and 2015 was significantly biased toward more dense commuting zones. STS wage growth hence appears to be the driving force behind fast wage growth in "superstar" cities.

The solid red line in the left panel of Figure 10 shows the wage-density gradient if average STS wages in each commuting zone had grown at the same rate as those of all other sectors within that commuting zone. Without STS the wage-density gradient would not have become any steeper since 1980, reflecting the density-bias in STS wage growth documented in Facts 1 and 3. Additionally, holding STS employment shares fixed at their 1980 level within each decile does not explain any of the steepening of the wage-density gradient. The absence of STS employment reallocation across

commuting zones helps explain this finding (cf. Fact 3).<sup>18</sup>

## 7.2 Aggregate Wage Inequality

We use a simple measure of wage inequality, the wage gap between the 90th and 50th percentile of the national wage distribution (“the 90/50 ratio” from here on), to assess the contribution of STS wage growth to the aggregate increase in wage inequality in the United States documented by Katz (1999), Autor et al. (2008), and others.<sup>19</sup>

Using U.S. Decennial Census data, in the right panel of Figure 10, we construct the wage distribution relative to the median worker’s wage for 1980 (blue) and 2010 (green), respectively. In 1980, a worker at the 90th percentile of the national wage distribution made 80% more than the median worker. In 2010, a worker at the 90th percentile of the wage distribution made 114% more than the median worker.

To assess the role of STS in the increase in the 90/50 ratio, we adjust STS wage growth to match all other sectors with the following deflator:

$$\text{STS Wage Growth Since 1980 / Non-STS Wage Growth Since 1980.}$$

Then we recompute the wage distribution for 2010 (solid red line). If STS workers had experienced the same wage increases as all other workers, the increase in the 90/50 ratio would be 32% smaller. Removing all STS workers from the workforce and recomputing the wage distribution among the remaining workers would lower the increase in the wage gap between the 90th and 50th percentiles of all workers by 47%.<sup>20</sup>

## 8. CONCLUDING REMARKS

For a long time, economists have treated “services” as one monolithic block of industries. However, industries within the service sector are extraordinarily heterogeneous. Since Autor and Dorn (2013), low-skill services and their fast employment growth have received increased attention in the litera-

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<sup>18</sup>In Figure A.12 in the Appendix, we show that the other high-skill sectors play no role in this. We re-do the decomposition from Figure 10, but substitute changes in the STS sector for changes in the Education and Medical sector; the wage-density gradient in 2015 remains unchanged. While medical wages have seen substantial growth, this growth was evenly dispersed across geography.

<sup>19</sup>We emphasize that we are not considering the role of tail distributions in inequality; see Smith, Yagan, Zidar and Zwick (2019) and Piketty and Zucman (2014) for studies that center on wages at the top 1% or 0.1% of the economy. The publicly available Census data are top-coded and not suitable for studying top income inequality.

<sup>20</sup>The numbers at the 95th percentile are similar. STS wage increases account for 32% of the increase in the wage gap between the 95th and 50th percentile of the wage distribution. If the STS sector disappeared completely, the increase in the wage gap between the 95th and 50th percentiles of all workers would be 42% smaller.

ture. We, in contrast, study high-skill services that are widely traded, and argue that these Skilled Tradable Services are central to understanding recent changes in the U.S. labor market.

We showed that these Skilled Tradable Services have exhibited patterns of wage and employment growth that resemble “superstar” dynamics, and set them apart from all other sectors. Rapid STS wage growth has been strikingly biased toward the most educated workers, the densest labor markets, and the most productive firms. Meanwhile, overall STS employment growth has been modest.

We outlined a theory that gets at the core of what these services do. Skilled Tradable Service workers provide knowledge inputs to other industries throughout the economy, but communication frictions limit such knowledge transmission. We argue that new information technologies have drastically reduced these frictions, allowing the most productive workers, regions, and firms to expand their reach and earn disproportionate returns.

We also document the direct relevance of STS for two of the most striking developments in U.S. labor markets since the 1980s. First, we show that the density bias in STS wage growth accounts for the entire rise of “superstar” cities. Second, we demonstrate that about 30% of the aggregate increase in wage inequality is accounted for by the fast wage growth of STS and the sector’s increasing skill intensity. We believe that the study of the superstar dynamics in STS wage growth provides a new understanding of the substantial increase in the return to skill since the 1980s.

In the future, only the most skilled individuals, the densest labor markets, and the highest paying firms are likely to participate in the growth of Skilled Tradable Services directly. As these services overtake traditional sectors like manufacturing as the new propulsive force in the U.S. economy, the exclusive nature of their growth poses new challenges to policymakers. We hope that this paper and the facts it documents will lead to increased attention and investigation of Skilled Tradable Services and their role in the U.S. economy.

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# APPENDIX

This appendix contains additional details on our data sources plus supplementary figures in Section A and details on the derivation of the model in Section B.

## A. DETAILS ON DATA AND SUPPLEMENTARY FIGURES

### A.1 Additional Details on Data Sources and Measurement

#### A.1.1 Quarterly Census of Employment and Wages

The Quarterly Census of Employment and Wages (QCEW) is a comprehensive data set of U.S. establishments published by the Bureau of Labor Statistics drawing on administrative data sources derived from state and federal unemployment insurance programs. The census covers 95% of all U.S. employment. A firm may have multiple establishments, each operating in a different industry and/or location. Conveniently, the BLS has reported the data on a consistent NAICS 2012 basis since 1990. While the data go back to 1975, earlier years use the SIC industry classification system so we restrict our analysis to the years between 1990 and 2016. We use the public-use version of the data set and extract industry level employment and payroll data. We define annual industry-level wages as the average annual payroll paid out per worker.

#### A.1.2 Comparing and Reconciling Data Sources

Jointly, the LBD, the Decennial Census, and the QCEW data provide a comprehensive account of American workers and their employment. Each source has strengths and limitations.

The QCEW and LBD are both derived from large administrative databases covering legal employment. The advantage of such data is that industry identifiers are reliable as are employment and payroll counts. However, these databases are on an establishment level and do not report data on individual workers. The Decennial Census, on the other hand, is a self-reported nationally representative survey. Industry classifications reflect individuals' responses to the following prompt "Describe the activity at location where employed." While in theory this question is in line with the NAICS industry classification system, which classifies establishments by the activity conducted at a given location, in practice workers may answer wrongly. For example, workers in the Ford headquarters should report working in NAICS Code 551114 "Management of Companies" rather than NAICS Code 441110 "New Car Dealers." Comparing employment shares across sectors in the LBD, QCEW, and Decennial Census suggests that some respondents misreported STS industries as

other industries. Nevertheless, we rely on the Decennial Censuses, the only nationally and locally representative source of public-use micro data. We primarily use these data to relate STS wage and employment growth and wage growth patterns across educational groups known from previous research.

Workers are flexible between industries and/or occupations.<sup>21</sup> We primarily consider the industry of an employee in his/her principal place of work. So a sales clerk in a local Target would be classified as retail, a warehouse worker in a regional distribution warehouse would be classified as warehousing and transport, and the CEO at the global headquarters would be classified in the Management of Firms.

But this methodology has some limitations. For example, the home of Walmart-Bentonville-Arkansas, had less than 1% of Population Census respondents working in establishments that are involved in the Management of Firms, but nearly 20% in retail sales - nearly double the national average. Going by unemployment insurance data, the QCEW reports that 10% of the population works in Management of firms, and only 12.5% of the population works in retail sales. Even without the micro-data, it is clear that many employees who run global firms simply report the principal business line.<sup>22</sup>

Similarly, each of our data sets has slightly different coverage. The Population Census is representative of the entire population, and the QCEW covers the 95% of the population that pays into unemployment insurance. However, the LBD only covers 84% of all workers, missing large parts of mostly public-sector employees. This is an issue when measuring the education sector - a majority of primary teachers are employed by sub-state-level local governments.

### A.1.3 Other Data Sets

We use two other sources of data in the paper.

**Input-Output Data** To define Skilled Tradable Services, we use the Input-Output (IO) tables in producer prices provided by the Bureau of Economic Analysis (BEA) of the United States Department of Commerce, a U.S. government agency that provides official macroeconomic and industry statistics. We use the IO tables in producer prices for the years 1980 to 2017, which the BEA provides with consistent NAICS 2012 industry classifications. We also use these data to compute the trends in aggregate output and exports across industries.

**Yale College Graduation Statistics** In spring 2017, Yale's Office of Career Strategy (OCS) conducted the Class of 2017 First Destination Survey for Yale College. The survey was sent to the 1,396 graduates in the Class of 2017 and 1,290 graduates completed the survey within six months of graduation,

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<sup>21</sup>This is the central question underlying the Heckscher-Ohlin model of trade.

<sup>22</sup>This type of issue is elaborated on in Fort et al. (2018).

TABLE A.1: 2-DIGIT NAICS SERVICE INDUSTRIES

Service Industry (NAICS)	Code	Skilled	Tradable	STS
Wholesale Trade	42	✗	✓	✗
Retail Trade	44	✗	✗	✗
Transportation and Warehousing	48	✗	✓	✗
Information	51	✓	✓	✓
Finance and Insurance	52	✓	✓	✓
Real Estate and Rental and Leasing	53	✓	✓	✓
Professional, Scientific, and Technical Services	54	✓	✓	✓
Management of Companies and Enterprises	55	✓	✓	✓
Admin, Support, Waste Mgmt, and Remediation Services	56	✗	✗	✗
Educational Services	61	✓	✗	✗
Health Care and Social Assistance	62	✓	✗	✗
Arts, Entertainment, and Recreation	71	✗	✗	✗
Accommodation and Food Services	72	✗	✗	✗
Other Services (except Public Administration)	81	✗	✗	✗

*Notes:* Tradability is determined using data from the Input-Output tables in producer prices for 2012 published by the Bureau of Economic Analysis. Skill intensity is determined using the public-use files of the 2010 American Community Survey obtained from IPUMS (see Ruggles et al. (2015)). Education gross value output is adjusted using local and state education expenditures from the 2012 Census of Governments.

creating a 92.4% response rate. It is important to note that not every respondent answered every question. It is also notable that a very small number of respondents reported more than one destination after graduation, such as an individual working full-time while attending graduate school part-time. For the statistics on first destinations, we chose the first location reported. In instances where location was blank or the location was outside the U.S., we dropped the individual from the sample. Similarly, for the reported industry statistics, if the industry was blank, either because the responder refused to answer, is engaged in further education, or is unemployed, we dropped the individual from the sample. There is no reason to suspect that graduates moving to certain destination locations or working in certain destination industries are more likely to leave survey fields blank. We use these data to compute the statistics cited in the introduction.

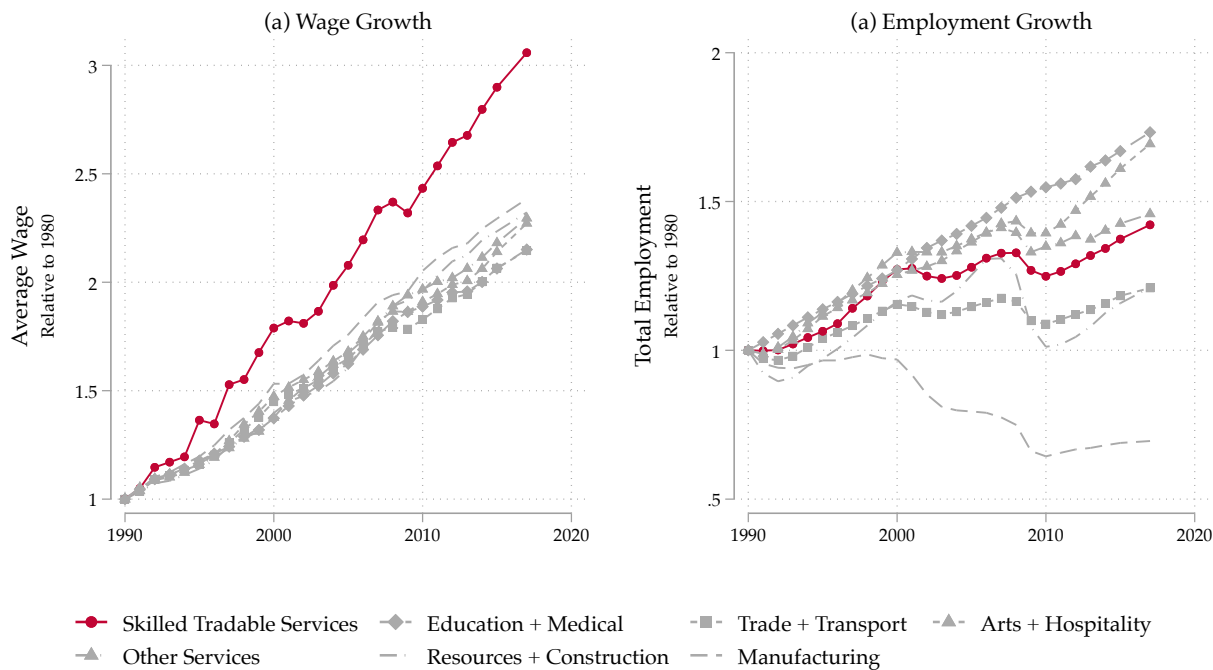
#### A.1.4 Service Sectors and Skilled Tradable Services

Figure A.1 lists all 2-digit NAICS 2012 service industries. We also list whether according to our measure of skill intensity and tradability, each sector is skilled, tradable, or both.



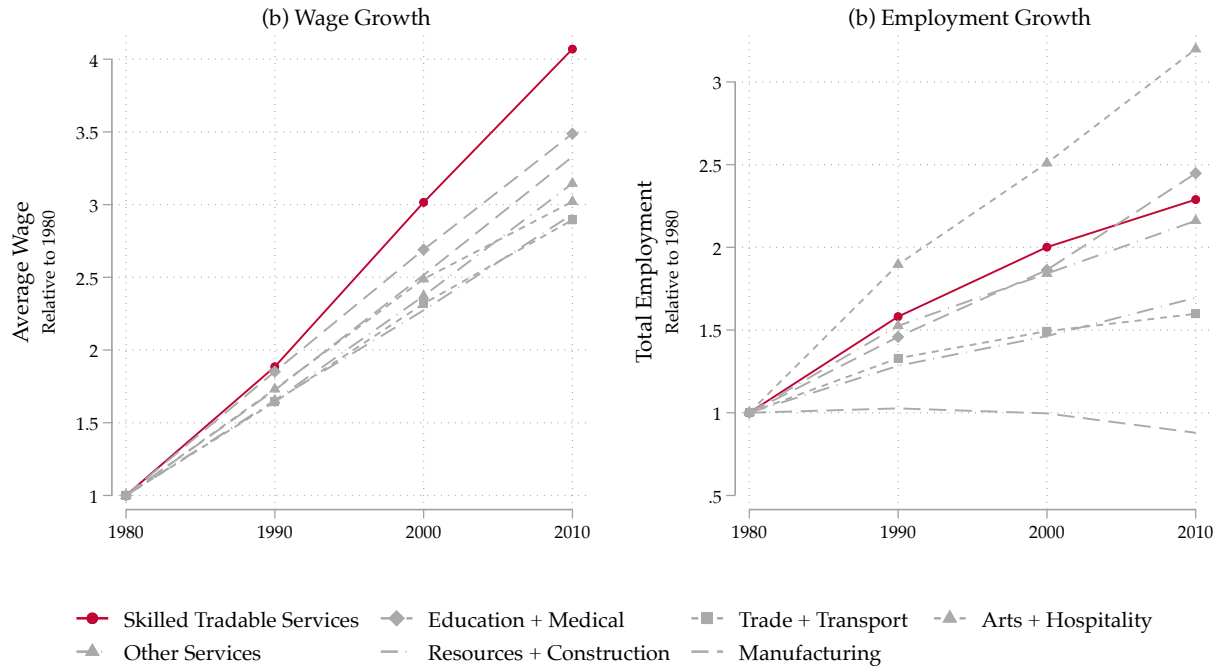
## A.2 Supplementary Figures

FIGURE A.1: WAGE AND EMPLOYMENT GROWTH BY SECTOR IN THE QCEW



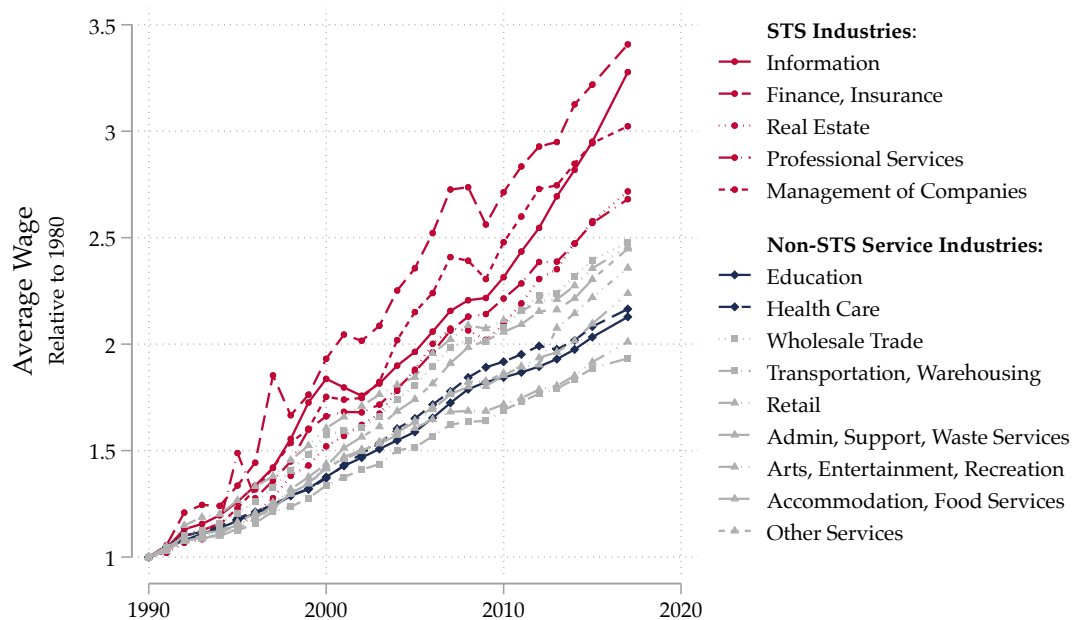
*Notes:* This figure replicates Figure 2 from the main body of the text. The right panel shows growth in employment from 1990 through 2017. The left panel shows the growth of average nominal wages by sector from 1990 through 2017. The data underlying the figure come from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). Average wages at the sectoral level are computed via aggregating payroll over all establishments within each sectoral grouping and each year, and dividing by total employment in the sector in that year. These are then normalized within sector by dividing by the average sectoral wage in 1990. Employment is calculated by aggregating the employment of all establishments with each sector, and then normalized within sector by dividing by total employment in 1990. We use the annual QCEW files from 1990-2017 that have been prepared by Bureau staff to have consistent industry codes. Data prior to 1990 exist with a different industrial classification system.

FIGURE A.2: WAGE AND EMPLOYMENT GROWTH BY SECTOR IN THE DECENNIAL CENSUS



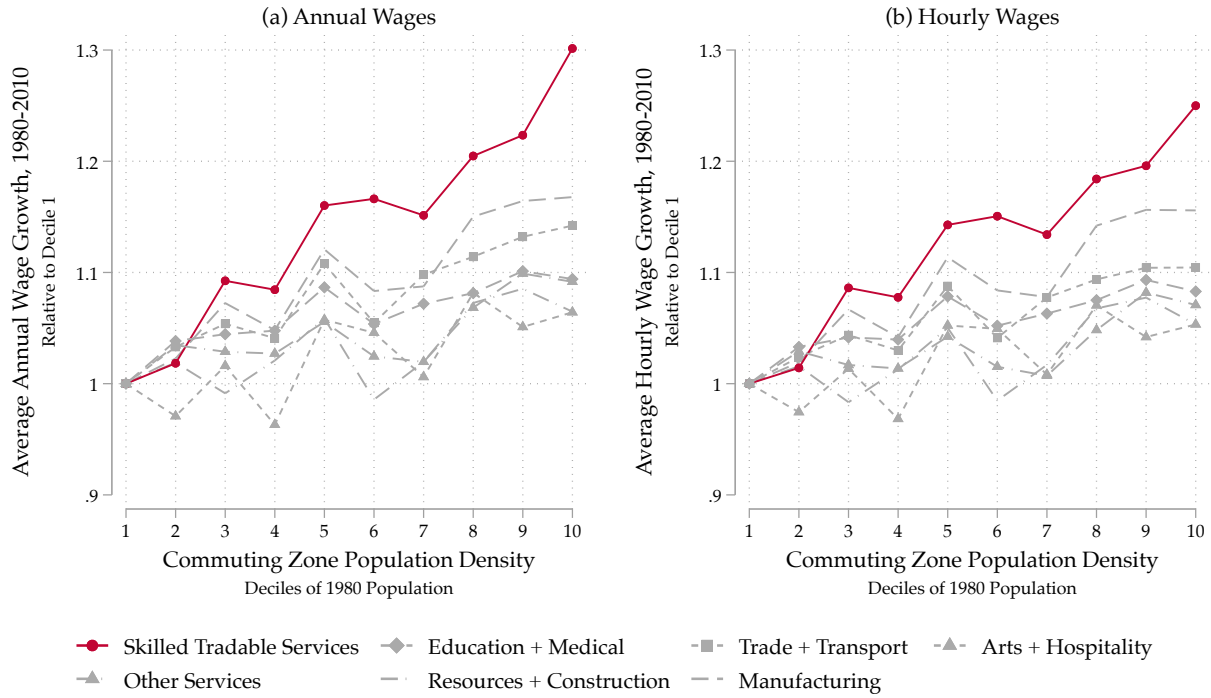
*Notes:* This figure replicates Figure 2 in the main body of the text using the Population Census. The left panel shows annual average wages by sector over time relative to 1980. The right panel shows total employment by sector relative to 1980. To construct the figure we use Decennial Census micro-data for 1980, 1990, and 2000, and micro-data from the American Community Survey for 2010, all made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual; employment is all workers in part-time or full-time employment in the sector for some part of the year. We weight observations using the Census sample weights. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define Skilled Tradable Services and other sector groupings.

FIGURE A.3: WAGE GROWTH BY 2-DIGIT NAICS SECTOR IN THE QCEW



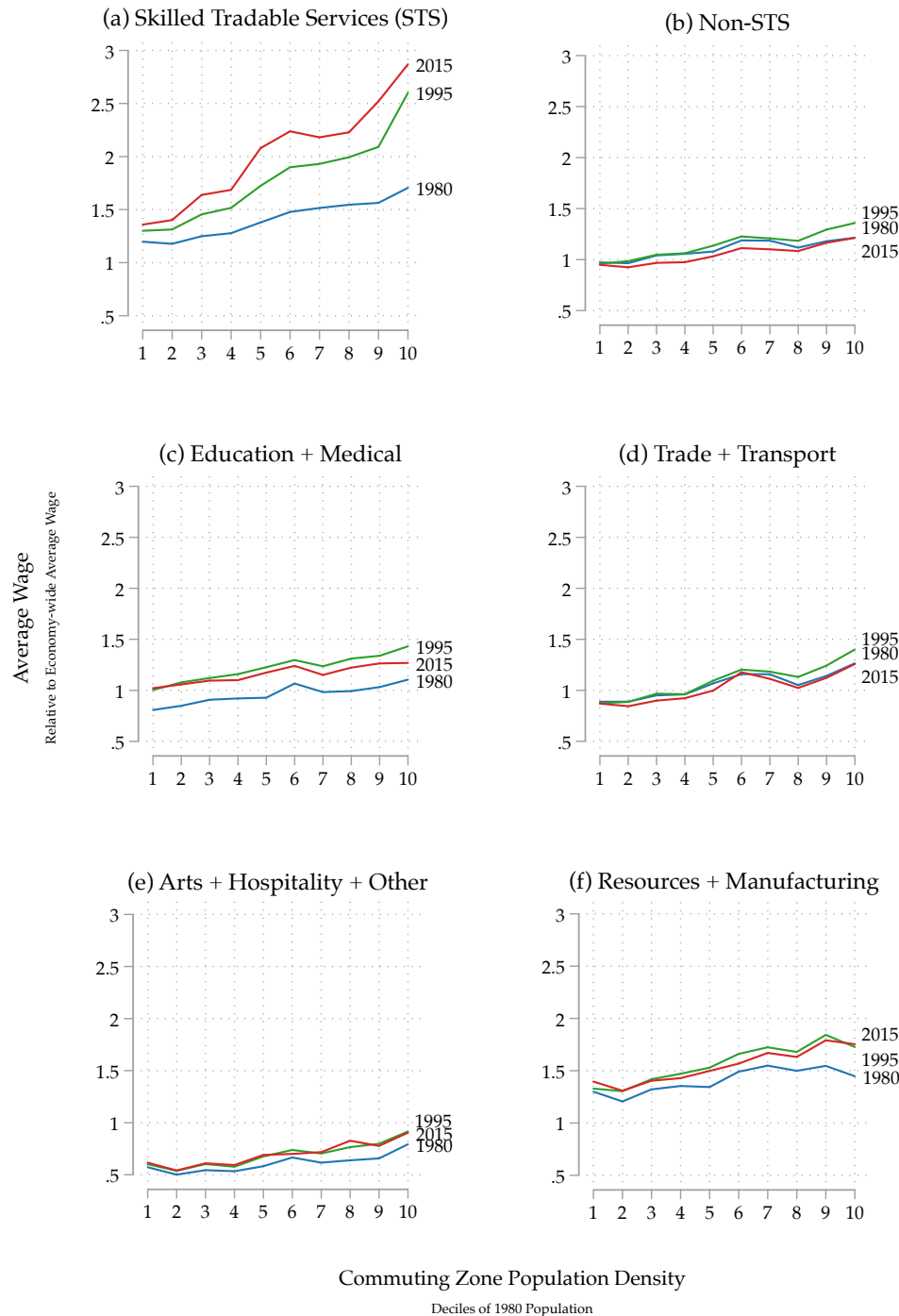
*Notes:* This figure shows the growth of average nominal wages by sub-sector from 1990 through 2017 for all 2-digit NAICS service industries. The data underlying the figure come from the Quarterly Census of Employment and Wages (QCEW). Average wages at the sectoral level are computed via aggregating payroll over all establishments within each sub-sectoral grouping and each year, and dividing by total employment in the sub-sector in that year. These are then normalized within sector by dividing by the average sectoral wage in 1990. Data points in red indicate STS industries. Blue data points indicate skilled, but non-traded industries.

FIGURE A.4: HOURLY AND ANNUAL WAGE GROWTH BY SECTOR  
AND COMMUTING ZONE POPULATION DENSITY



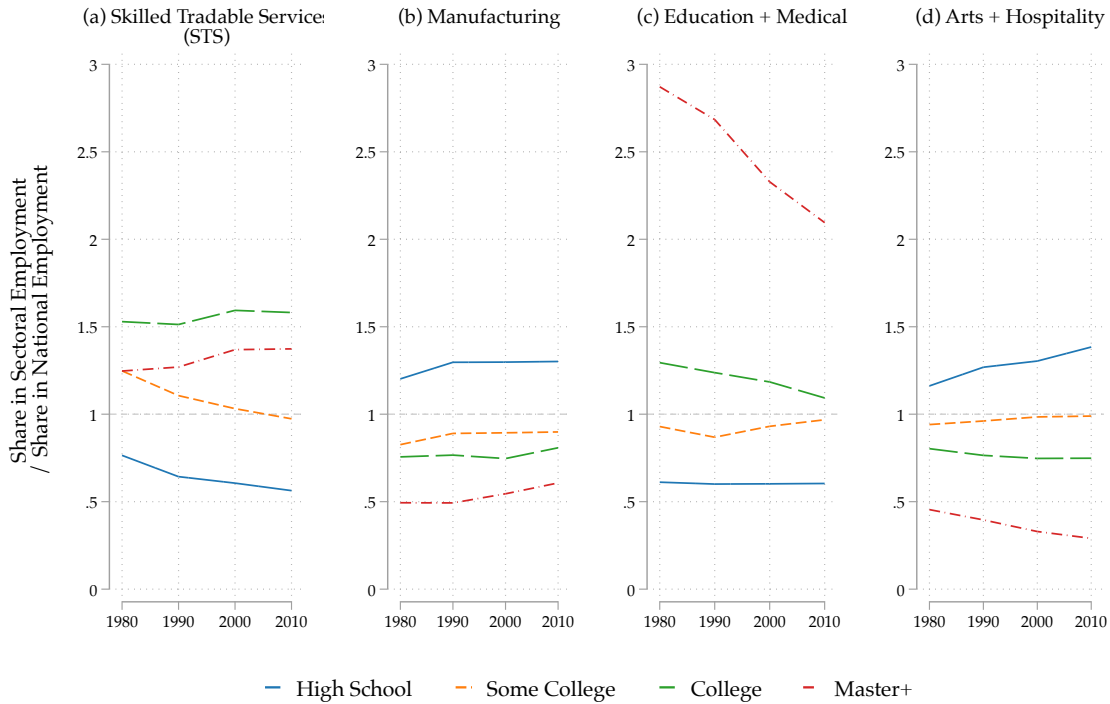
*Notes:* The left panel of this figure replicates the left panel of Figure 4 in the main text using the Population Census data. The right panel replicates the left panel but with average hourly wages within each sector rather than average annual wage, again using the Population Census data. The left panel shows average annual wage growth by sector between 1980 and 2010 across commuting zones ordered by 1980 population density and grouped into deciles of employment. The right panel shows average hourly wage growth by sector between 1980 and 2010 across commuting zones ordered by 1980 population density and grouped into deciles of employment. To construct the figure we use Decennial Census micro-data for 1980, 1990, and 2000, and micro-data from the American Community Survey for 2010, all made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual; employment is all workers in part-time or full-time employment in the sector for some part of the year. To construct the x-axis, we order the 741 commuting zones (see Section 2) in the United States by their population density in 1980. Then we group commuting zones together, starting with the least dense, into ten groups that each account for 10% of U.S. employment in 1980. To construct average hours worked by sector, we multiply “Usual hours worked per week” or “Hours worked last week” times “Weeks worked last year” for each observation and then take averages within sector and commuting zone decile. We then divide average annual wage within sector and commuting zone decile by average hours worked within that bin to obtain a measure of hourly wage. We weight observations using the Census sample weights. We map the Census’ industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define Skilled Tradable Services and other sector groupings.

FIGURE A.5: RELATIVE WAGES BY SECTOR,  
COMMUTING ZONE POPULATION DENSITY, AND YEAR



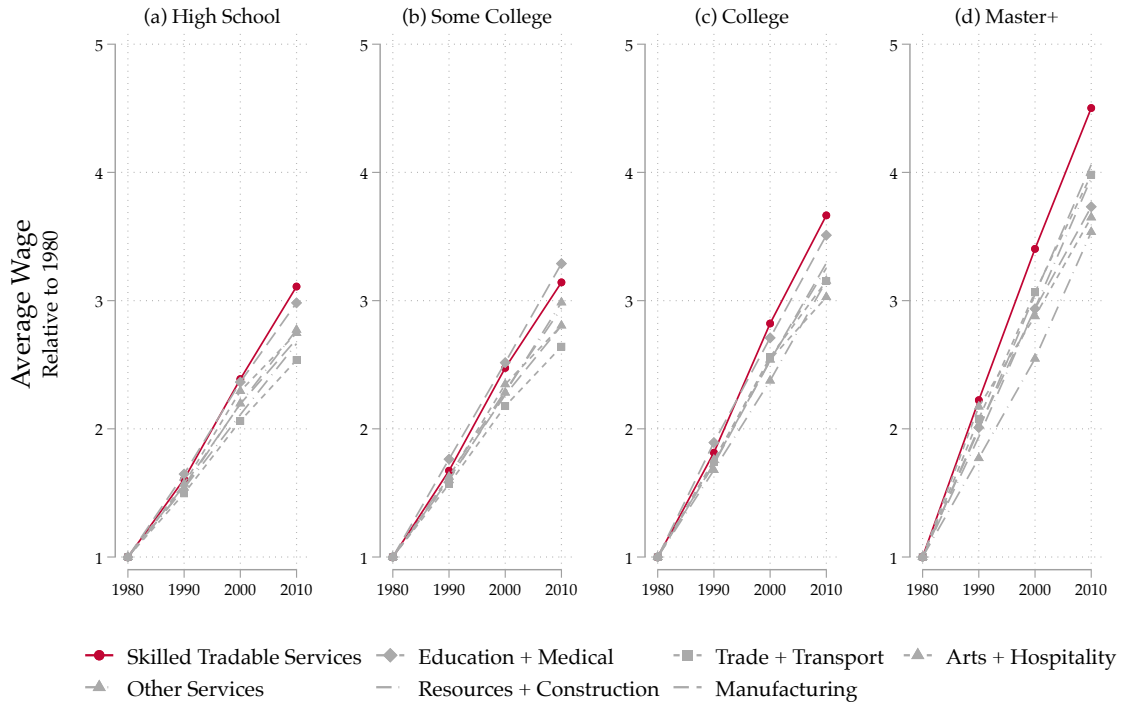
Notes: This figure shows how average wages within sector each have evolved over different commuting zone densities for the years 1980, 1995 and 2015. The data underlying the figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). 1980 population figures are taken from the Decennial Census and commuting zone boundaries are from Tolbert and Sizer (1996). Commuting zone deciles are constructed by ordering all commuting zones (cf. Section 2) by their population density in 1980 and then forming deciles of increasing density each containing commuting zones that jointly account for 10% of the national population in 1980. Average wages at the sectoral and commuting zone decile level are computed via aggregating payroll over all establishments within that grouping and each year, and dividing by total employment in the grouping in that year. These are then normalized within each year by dividing by the economy-wide average wage in that year. 1980 population figures and commuting zone boundaries are taken from the Census, and we use these populations to calculate 10 deciles of commuting zone density. We assign each establishment in the LBD a commuting zone density decile via the zip code in which each establishment is located.

FIGURE A.6: EMPLOYMENT SHARES OF EDUCATION GROUPS WITHIN SECTORS RELATIVE TO EMPLOYMENT SHARES OF EDUCATION GROUPS IN AGGREGATE ECONOMY



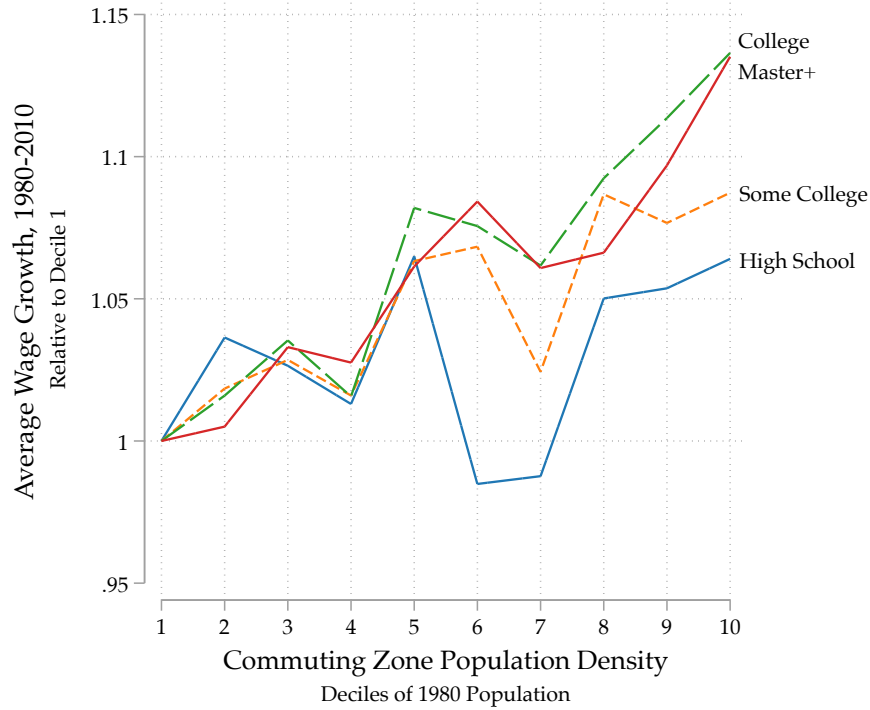
*Notes:* This figure shows the fraction of the work force within each sector that comes from one of four educational attainment groups (High School, Some College, College, Master+) relative to the employment share of that educational attainment group in the national economy in that year for the United States for each decade between 1980 and 2010. To construct the figure we use Decennial Census micro-data for 1980, 1990, and 2000, and micro-data from the American Community Survey for 2010, all made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. Employment is all workers in part-time or full-time employment in the sector for some part of the year. We group the education identifiers in the Census micro-data into four groups: High School, Some College, College, Master+. We drop individuals with missing education information. We weight observations using the Census sample weights. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define Skilled Tradable Services and other sector groupings.

FIGURE A.7: WAGE GROWTH BY SECTOR AND EDUCATION GROUP



*Notes:* This figure replicates the left panel of Figure 2 in the main body of the paper separately for four different groups of educational attainment (High School, Some College, College, Master+) using the Population Census data. For the respective groups the panels show annual average wages by sector over time relative to 1980. To construct the figure we use Decennial Census micro-data for 1980, 1990, and 2000, and micro-data from the American Community Survey for 2010, all made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We group the education identifiers in the Census micro-data into four groups: High School, Some College, College, Master+. We weight observations using the Census sample weights. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define Skilled Tradable Services and other sector groupings.

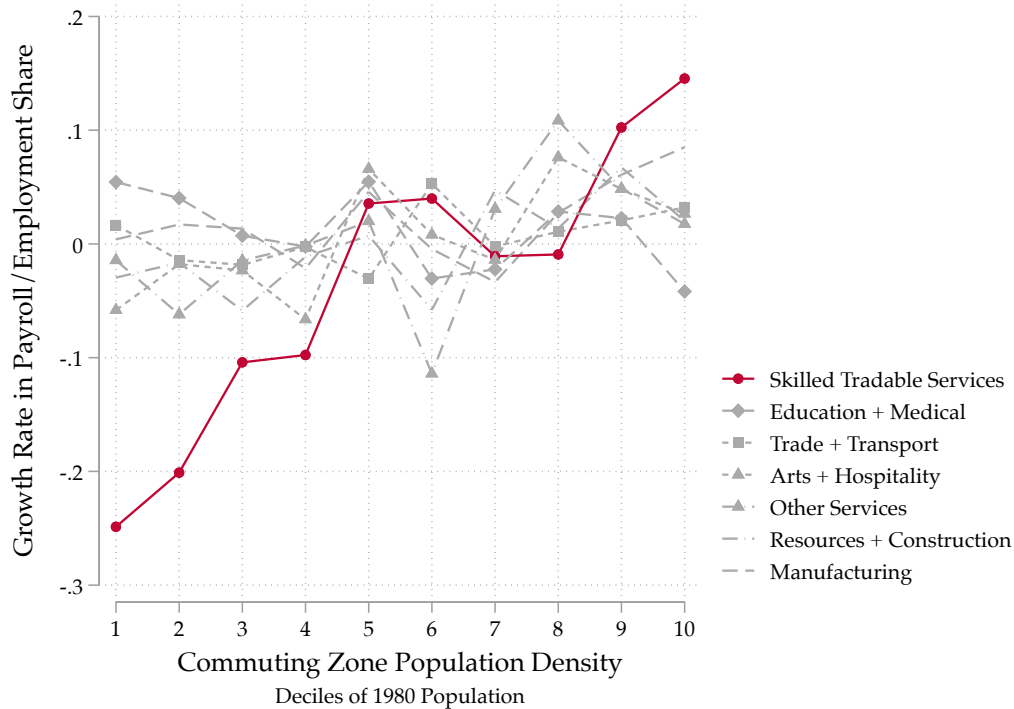
FIGURE A.8: WAGE GROWTH BY EDUCATION LEVEL AND  
COMMUTING ZONE POPULATION DENSITY



*Notes:* The figure shows growth in averages wages for four educational attainment groups (High School, Some College, College, Master+) across commuting zones of increasing density. To construct the figure we use Decennial Census micro-data for 1980, 1990, and 2000, and micro-data from the American Community Survey for 2010, all made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual; employment is all workers in part-time or full-time employment in the sector for some part of the year. To construct the x-axis, we order the 741 commuting zones (see Section 2) in the United States by their population density in 1980. Then we group commuting zones together, starting with the least dense, into ten groups that each account for 10% of U.S. employment in 1980. We weight observations using the Census sample weights. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define Skilled Tradable Services and other sector groupings.

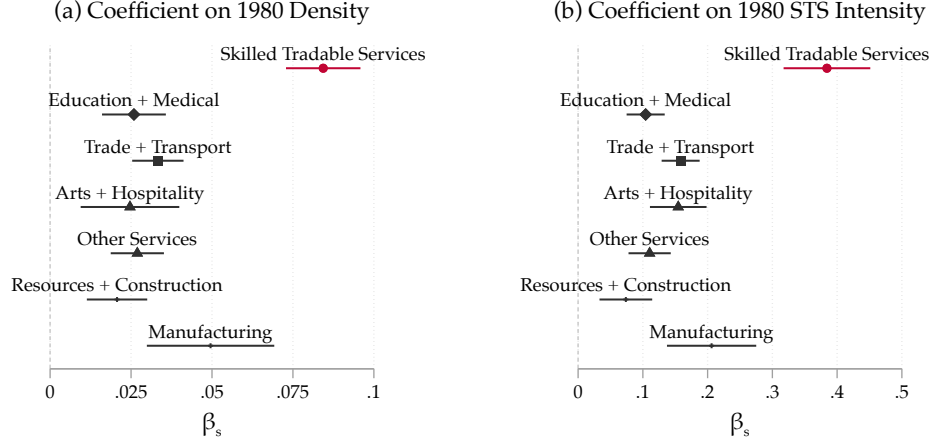


FIGURE A.9: PAYROLL REALLOCATION BY SECTOR AND  
COMMUTING ZONE POPULATION DENSITY



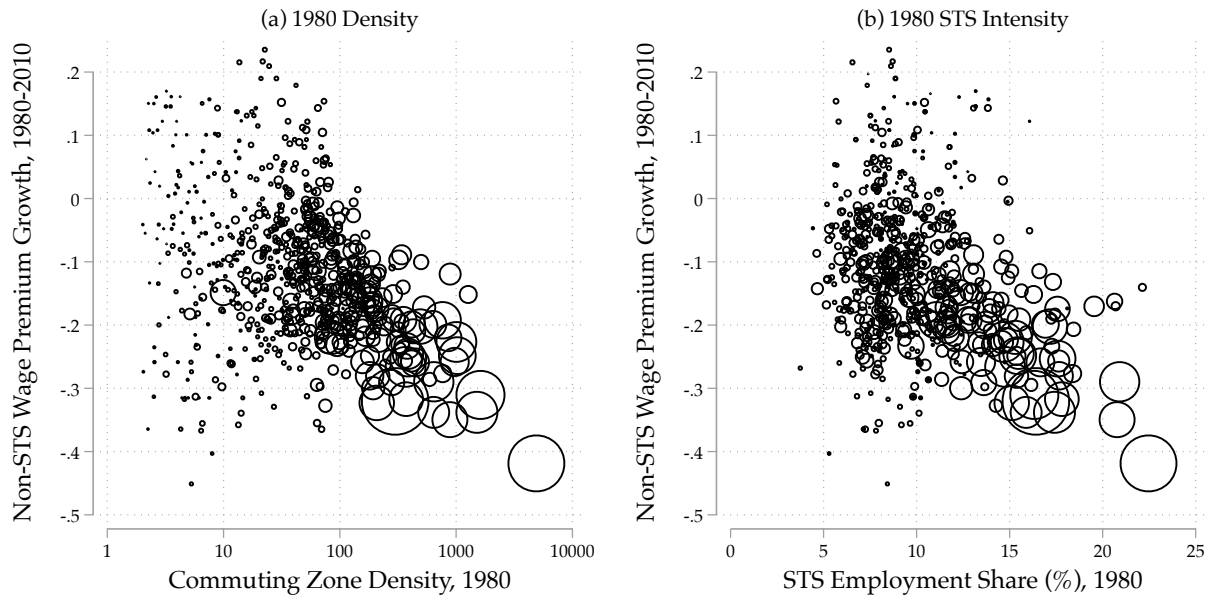
*Notes:* The figure shows the growth in the ratio of a commuting zone's share in national payroll of a sector relative to its share in the national employment of that sector between 1980 and 2010 for commuting zones of increasing density. The data underlying this figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). 1980 population figures are taken from the Decennial Census and commuting zone boundaries are from Tolbert and Sizer (1996). Commuting zone deciles are constructed by ordering all commuting zones (cf. Section 2) by their population density in 1980 and then forming deciles of increasing density, each containing commuting zones that jointly account for 10% of the national population in 1980. Decile 1 contains the least dense commuting zones, decile 10 the densest commuting zones. Total payroll at the sectoral and commuting zone decile level is computed by aggregating payroll over all establishments within each sectoral grouping, commuting zone decile and year. Total employment is computed in a similar way. We then aggregate payroll and employment across all commuting zone deciles within each sector and compute each decile's share in the national sectoral payroll and employment. Growth is calculated as the percentage change in this measure between 1980 and 2015. We assign each establishment in the LBD a commuting zone density decile via the zip in which code each establishment is located.

FIGURE A.10: REGRESSION OF COMMUTING ZONE WAGE CHANGE  
ON INITIAL COMPARATIVE ADVANTAGE BY SECTOR



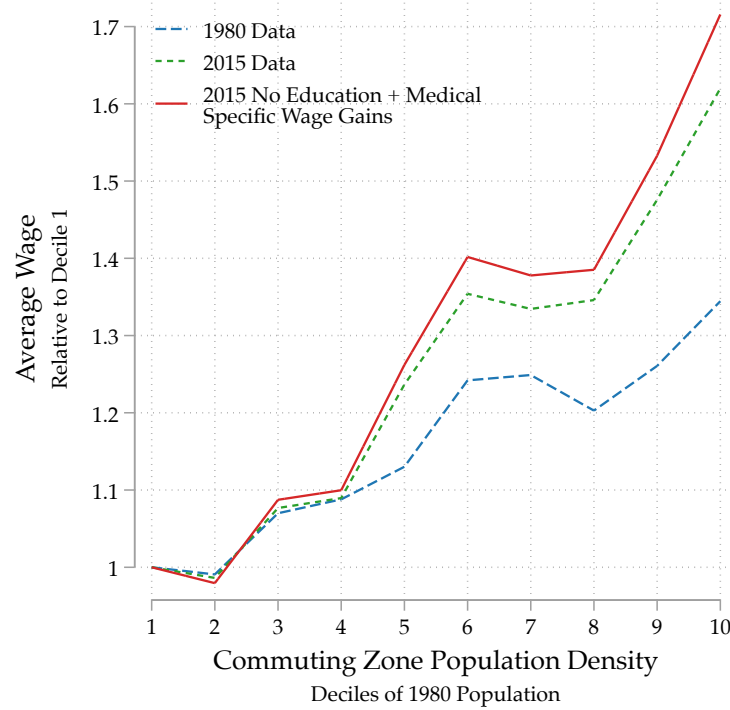
*Notes:* This figure graphically shows results for  $\beta_s$  from Equation 7 with changes in sectoral wages as outcome. These coefficients represent the interaction of a sectoral dummy with two measures of STS comparative advantage. The left panel measures comparative advantage using the 1980 density of a commuting zone. The right panel measures comparative advantage using the 1980 STS employment share of a commuting zone. Robust standard errors with 1980 population weights. Confidence intervals are computed at the 95% two-sided level. Full regression results are available in the online appendix. To construct the figure we use Decennial Census micro-data for 1980, and micro-data from the American Community Survey for 2010, made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We use the Census sample weights to construct the income distribution. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define the Skilled Tradable Services sector.

FIGURE A.11: CHANGE IN COMMUTING ZONE SKILLED TRADABLE SERVICES (STS) WAGE  
BY INITIAL COMPARATIVE ADVANTAGE



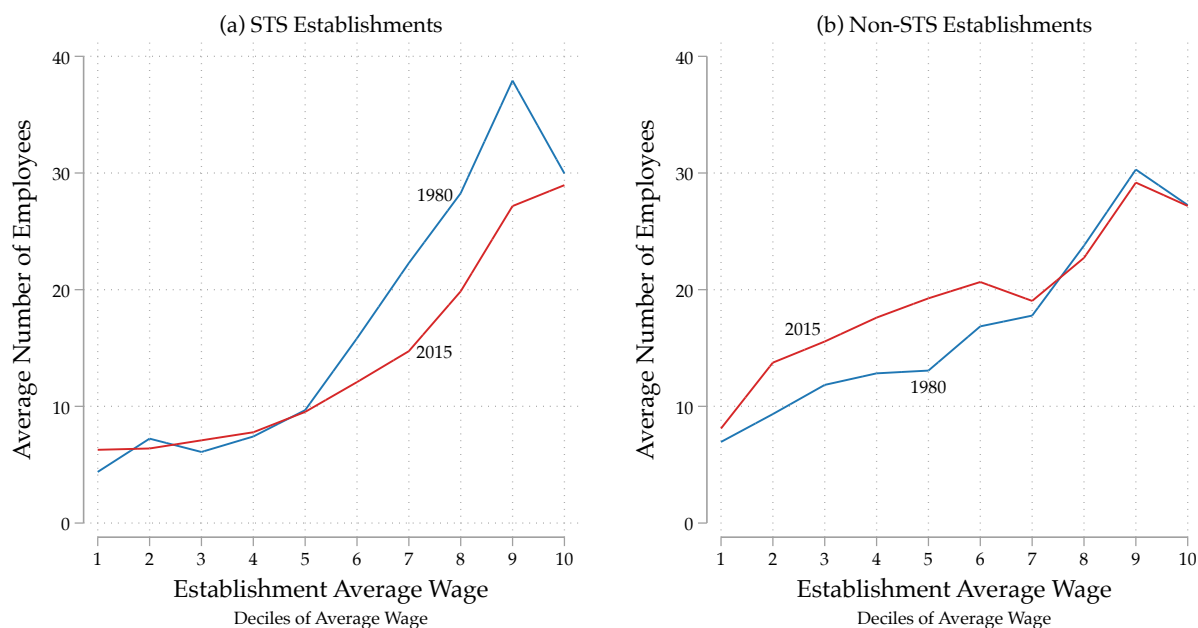
This figure shows changes in the within-commuting-zone non-STs wage from 1980-2015 as a function of pre-existing indicators of STS comparative advantage. The left panel uses the 1980 population density as a measure of STS comparative advantage. The right panel uses the 1980 STS employment share as a measure of STS comparative advantage. The size of the circles indicates the 1980 population of the commuting zones. To construct the figure we use Decennial Census micro-data for 1980, and micro-data from the American Community Survey for 2010, made available by Ruggles et al. (2015). We restrict the sample to individuals between age 16 and 64 who worked in the year preceding the survey. The wage measure is total pre-tax wage and salary income of an individual. We use the Census sample weights to construct the income distribution. We map the Census' industry identifiers to 2-digit NAICS codes and group codes as discussed in Section 3 to define the Skilled Tradable Services sector.

FIGURE A.12: EDUCATION AND MEDICAL SERVICES AND  
THE RISE OF SUPERSTAR CITIES



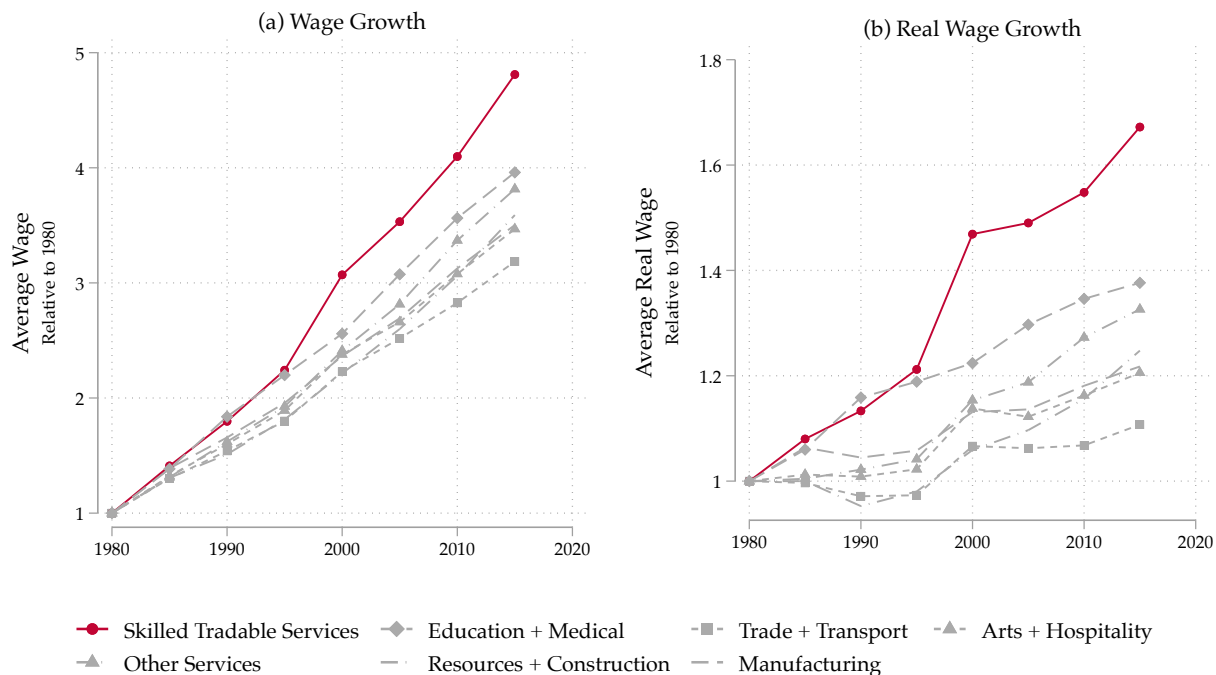
*Notes:* The figure shows that the wage-density gradient has increased substantially since 1980. The solid red line shows what the density wage premium would be without wage growth in the Education and Medical sector. The data underlying the figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). 1980 population figures are taken from the Decennial Census and commuting zone boundaries are from Tolbert and Sizer (1996). Commuting zone deciles are constructed by ordering all commuting zones (cf. Section 2) by their population density in 1980 and then forming deciles of increasing density each containing commuting zones that jointly account for 10% of the national population in 1980. Average wages at the sectoral and commuting zone decile level are computed by aggregating payroll over all establishments within each sectoral grouping, commuting zone decile and year, and dividing by total employment in that group in that year. Last, we normalize the wage rates relative to the first commuting zone decile within each sectoral group. We assign each establishment in the LBD a commuting zone density decile via the zip code in which each establishment is located.

FIGURE A.13: AVERAGE NUMBER OF EMPLOYEES IN SKILLED TRADABLE SERVICES (STS) AND THE REST OF THE ECONOMY (NON-STs) BY ESTABLISHMENT AVERAGE WAGE



*Notes:* The figure shows average establishment employment size within deciles of establishment-level average wage for the Skilled Tradable Services (STS) sector and the rest of the economy (non-STs) for 1980 and 2015. The data underlying this figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). In each year, we rank all establishments by their average wage and then construct deciles that each account for 10% of establishments. The average number of employees within deciles and year is computed by aggregating employment over all establishments within each decile and year, and dividing by the total number of establishments in that group in that year.

FIGURE A.14: WAGE AND REAL WAGE GROWTH BY SECTOR



Notes: The left panel shows the growth in average wages by sector and commuting zone density between 1980 and 2015. The right panel does the same for nominal wages deflated by the consumer price index for all urban consumers (CPI-U). The data underlying this figure come from the Longitudinal Business Database (LBD). We map industry identifiers to a consistent NAICS-2 basis using the crosswalk in Fort and Klimek (2016). Average wages at the sectoral level are computed by aggregating payroll and employment over all establishments within each sectoral grouping and year, and then dividing the former by the latter. The wage measure is normalized within sector by dividing by the average sectoral wage in 1980.

## B. ADDITIONAL MODEL DERIVATIONS

**The only teams that form have high-skill managers and low-skill workers** The basic insight is that teams form if they generate a surplus. We show that the only teams that generate an economic surplus are teams with high-skill managers and low-skill workers.

The expected output of a team of low-skill managers managing a group of low-skill workers is  $nq_L$ . If, instead, all participants on this team worked by themselves output would be  $(n + 1)q_L$ . As a result, such a team does not form in equilibrium. High-skill manager/high-skill worker teams never form for analogous reasons.

Now suppose a low-skill manager directed a group of high-skill workers. Together, the team would produce an expected output of  $nq_H$ , whereas the same group of workers could produce  $nq_H + q_L$  if each was working alone. In consequence, such teams do not form in equilibrium.

Consider a team of low-skill workers reporting to a high-skill manager. Jointly, such a team produces an expected output of  $nq_H$ , while, when working individually, they could only produce an expected output of  $nq_L + q_H$ . But then clearly for some  $n$

$$nq_H > nq_L + q_H \Rightarrow \frac{(n-1)}{n}q_H > q_L \quad (\text{A.1})$$

holds since  $q_H > q_L$ . Recall from equation 1 that an optimal team has size:

$$n = \frac{1}{(1 - q_L)h},$$

which shows that for low-enough communication costs,  $h$ ,  $n$  becomes large enough to make equation A.1 hold, and teams form in equilibrium.

**Existence of High Communication Cost Equilibrium** A number of conditions need to hold for this equilibrium to prevail as described in the text:

1. High-skill workers are sufficiently abundant in the dense location that they cannot all form teams.
2. It is profitable to form teams in the dense city.
3. It is unprofitable to form teams in the sparse city.
4. It is not profitable to form cross-region teams at all.

First, note that in this equilibrium, high-skill wages are equalized across regions. We derived the expression for the optimal team size,  $n^D$ , in equation 2. Workers in the dense location are sufficiently

abundant relative to low-skill workers if they cannot all form teams, i.e., if the following inequality holds:

$$m_L^D < m_H^D \times n^D. \quad (\text{A.2})$$

The left-hand side is the actual number of low-skill workers in the location, and the right-hand side is the number of low-skill workers that would be needed to allow all high-skill workers to be managers.

Plugging the expression for optimal firm size into equation A.2, and using the fact that  $m_H^D = M^H/2$ , since high-skill wages are equalized across regions, we obtain:

$$m_L^D < \frac{M_H}{2}(1 - q_L)h^D. \quad (\text{A.3})$$

Condition A.3 ensures a sufficient abundance of high-skill workers in the dense city.

It is optimal to form a team in the dense city, as long as low-skill workers are willing to participate (high-skill workers are always indifferent, since they are abundant). Low-skill workers want to form teams if they earn at least as much as outside of a team, given that high-skill managers need to obtain  $q_H$ :

$$q_H(1 - (1 - q_L)h^D) \geq q_L, \quad (\text{A.4})$$

where the left-hand side is the low-skill wage in a team derived in equation 4 in the text, and the right-hand side is the low-skill wage outside a team. Condition A.4 ensures that teams do form in the dense city. It also pins down the level of within-region communication costs,  $\bar{h}^D$ , below which teams form within the dense city:

$$\bar{h}^D = \frac{q_H - q_L}{q_H - q_H q_L}.$$

In practice, we assume that low-skill workers are abundant relative to high-skill workers in the sparse city. Mirroring equation A.3, this holds as long as:

$$m_L^S > \frac{M_H}{2}(1 - q_L)h^S. \quad (\text{A.5})$$

But then, it can be shown that high-skill workers would earn the following if they ran a team of low-skill workers:

$$w_H^S = \frac{(q_H - q_L)}{(1 - q_L)h^S}.$$

So teams do not form in the sparse location as long as:

$$\frac{(q_H - q_L)}{(1 - q_L)h^S} < q_H. \quad (\text{A.6})$$

As long as conditions A.5 and A.6 hold, no teams form in the sparse city. We can use expression A.6



to derive a cutoff,  $\bar{h}^S$ , for no teams to form in the sparse location given by:

$$\frac{(q_H - q_L)}{(1 - q_L)h^S\tau} = q_H \Rightarrow \bar{h}^S = \frac{(q_H - q_L)}{(1 - q_L)q_H}.$$

Last, note that since  $\tilde{h}^c > h^c$  no cross-regional teams would ever be profitable with managers in the sparse region as long as conditions A.5 and A.6 are satisfied. Finally, note that none of the previous conditions implicate the parameter  $\tau$ .  $\tau$  can always be chosen large enough for cross-regional teams to be un-profitable. To see this compare the surplus from a cross-regional team to the surplus from those workers working individually (right-hand side):

$$q_H \frac{1}{(1 - q_L)\tau h^D} < q_H + q_L \frac{1}{(1 - q_L)\tau h^D} \Rightarrow (q_H - q_L) \frac{1}{(1 - q_L)\tau h^D} < q_H$$

But then for  $\tau \rightarrow \infty$  this equation always holds and no cross-regional trade occurs for any value of the remaining parameters.

Now we show that conditions A.3-A.6 hold simultaneously so that the high-cost equilibrium can exist. A.3 is always satisfied for large enough  $M_H$ . Condition A.5 is always satisfied for large enough  $m_L^S$ . Finally, condition A.4 is satisfied for low enough  $h^D$  and condition A.6 for high enough  $h^S$ . Hence there exists a set of parameters that make the equilibrium described in the text prevail.

**Existence of High to Low Communication Cost Equilibrium** For this equilibrium to follow from the equilibrium described in the previous section as  $\tau$  falls the following restrictions have to hold:

1. There are no local teams formed in the sparse region.
2. There are local and cross-border teams formed in the dense city.
3. Low-skill workers are abundant enough in the economy so that all high-skill workers in the dense location can form either local or cross-region teams in equilibrium.

A.5 and A.6 still ensure that no local teams form in the sparse region. In fact, if wages for high-skill workers increase in the dense location, more of them will move there, further lowering the number of high-skill workers in the sparse region below  $m_H^S = \frac{M_H}{2}$ . As a result, condition A.5 is even more easily satisfied.

Consider low-skill workers in the sparse city: they are happy to work for high-skill managers from the location for wage  $q_L$ . But then, high-skill workers in the location find it profitable to work with low-skill workers in the sparse location as long as:

$$w_H^D = \frac{(q_H - q_L)}{(1 - q_L)h^D\tau} \geq q_H. \tag{A.7}$$

Note that equation A.7 pins down the high-skill wage in the dense region, since it constitutes the reservation wage for high-skill workers that cannot form local teams. The possibility of interregional trade has lowered the outside option for high-skill workers in the dense city. Equation A.7 pins down the  $\bar{\tau}$  so that for all  $\tau < \bar{\tau}$  interregional trade in problems occurs:

$$\bar{\tau} = \frac{(q_H - q_L)}{(1 - q_L)h^D q_H}$$

Spatial equilibrium for high-skill workers then implies:

$$\frac{q_H}{(M_H - m_H^D)^\eta} = \frac{q_H - q_L}{(1 - q_L)h^D \tau (m_H^D)^\eta},$$

which has to hold for indirect utilities to be equalized across space, and using the adding up condition for high-skill worker supply. This equation can be solved for the mass of high-skill workers in the dense region:

$$m_H^D = \frac{(q_H - q_L)^{\frac{1}{\eta}}}{(q_H(1 - q_L)h^D \tau)^{\frac{1}{\eta}} + (q_H - q_L)^{\frac{1}{\eta}}}.$$

Now we can compute the total demand for low-skill workers in the sparse location from high-skill managers in the dense city. We multiply the number of high-skill workers in the dense location that are not needed to form local teams by the optimal firm size for interregional teams, to obtain the following restriction on the supply of low-skill workers in the sparse city:

$$m_L^S > (m_H^D - \frac{m_L^D}{n^D}) \times n_{CR}^D \Rightarrow m_L^S > \frac{\frac{(q_H - q_L)^{\frac{1}{\eta}}}{(q_H(1 - q_L)h^D \tau)^{\frac{1}{\eta}} + (q_H - q_L)^{\frac{1}{\eta}}} - m_L^D(1 - q_L)h^D}{(1 - q_L)h^D \tau} \quad (\text{A.8})$$

As discussed above, A.5 and A.6 hold given the conditions described in the text for the high  $\tau$  equilibrium. A.7 holds as long as  $\tau < \bar{\tau}$ . Note also that there is a  $1 < \tau < \bar{\tau}$  such that this holds because we can choose  $h^D$  arbitrarily low without violating any of the previous parameter conditions. Last, note that condition A.8 can be made to hold by choosing  $m_L^S$  large enough, which does not violate any previous parameter conditions either. In summary, there are values in the parameter space for which lowering  $\tau$  from  $\tau > \bar{\tau}$  to  $\tau < \bar{\tau}$  produces the two equilibria described in the main body of the text.

**Comparative Statics Results** In this section, we compute closed-form solutions for some endogenous objects as a function of the interregional communication costs  $\tau$ . We show the following in order:

1. As  $\tau$  falls, wages for workers specializing in knowledge work grow faster than those of other workers.
2. As  $\tau$  falls, real wages for low-skill workers fall.
3. As  $\tau$  falls, employment of workers specializing in knowledge work rises.
4. As  $\tau$  falls, the employment share in specialized knowledge work among high-skill workers rises.
5. As  $\tau$  falls, the skilled wage premium in the economy increases.
6. Knowledge workers earn more initially before  $\tau$  falls.
7. As  $\tau$  falls, high-skill workers move into the dense city.
8. As  $\tau$  falls, wages for specialized knowledge work in the dense location rise, despite high-skill workers moving in.

For simplicity we call workers specialized in knowledge work STS workers.

As  $\tau$  drops below  $\bar{\tau}$ , STS workers in the dense location move from earning  $w_H^D = q_H$  to earning  $w_H^D = \frac{(q_H - q_L)}{(1 - q_L)h^D\tau} \geq q_H$ . Also note that as  $\tau$  keeps falling  $w_H^D = \frac{(q_H - q_L)}{(1 - q_L)h^D\tau}$  keeps rising. The wages of workers in the sparse region are fixed at  $q_H$  and  $q_L$  for high- and low-skill workers, respectively. Low-skill workers in the dense location earn  $w_L^D = q_H(1 - (1 - q_L)h^D)$  for  $\tau > \bar{\tau}$  and earn  $w_L^D = \frac{n^D q_H - \frac{(q_H - q_L)}{(1 - q_L)h^D\tau}}{n^D}$  for  $\tau < \bar{\tau}$ . Hence, their wage declines, since the surplus of forming a *local* team is unaffected by changes in  $\tau$  but the outside option of high-skill workers increases, allowing them to claim a larger share of the surplus from *local* teams. This establishes claims (1) and (2) in the above list.

For  $\tau > \bar{\tau}$  not all workers in the location work in STS since low-skill workers are scarce. At the same time, half of all high-skill workers live in the dense region. So fewer than  $\frac{M_H}{2}$  high-skill workers work in STS overall. As  $\tau$  falls below  $\bar{\tau}$ , all high-skill workers in the dense location form teams, either local or cross-region, and hence STS employment in the economy increases. Additionally,  $m_H^D = \frac{(q_H - q_L)^{\frac{1}{\eta}}}{(q_H(1 - q_L)h^D\tau)^{\frac{1}{\eta}} + (q_H - q_L)^{\frac{1}{\eta}}} > \frac{M_H}{2}$  so that the number of high-skill workers in the dense region increases further, further raising overall STS employment. By the same argument, the STS employment share among high-skill workers in the dense location rises as  $\tau$  falls below  $\bar{\tau}$ . By the same argument, the STS employment share among all high-skill workers rises as  $\tau$  falls below  $\bar{\tau}$ .

Since more high-skill workers move into STS work as  $\tau$  falls, the average wage among STS workers increases and is stable among other high-skill workers, and since the average low-skill worker earns less than before as  $\tau$  falls, the skill premium in the economy rises as  $\tau$  keeps falling below  $\bar{\tau}$ .

For  $\tau$  above  $\bar{\tau}$ , knowledge workers earn  $q_H$  in both regions, while low-skill workers earn  $q_L$  in the sparse region and  $w_L^D = q_H(1 - (1 - q_L)h^D)$  in the dense city. Note that  $w_L^D = q_H(1 - (1 - q_L)h^D) < q_H$  necessarily, so that low-skill workers earn less than high-skill workers before  $\tau$  falls.

The number of high-skill workers in the dense location for all  $\tau < \bar{\tau}$  is given by:

$$m_H^D = \frac{(q_H - q_L)^{\frac{1}{\eta}}}{(q_H(1 - q_L)h^D\tau)^{\frac{1}{\eta}} + (q_H - q_L)^{\frac{1}{\eta}}}$$

which is strictly decreasing in  $\tau$ . Hence as  $\tau$  falls further, more high-skill workers move into the city.

The wage of STS workers in the dense location for all  $\tau < \bar{\tau}$  is given by

$$w_H^D = \frac{(q_H - q_L)}{(1 - q_L)h^D\tau}$$

which is strictly decreasing in  $\tau$ . Hence as  $\tau$  falls further, the STS wage in the dense location rises further.