Domestic Offshoring in a Knowledge Economy*

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Abstract

During past decades, substantial skill and occupation relocation took place across U.S. cities: Big cities attract more skilled workers and become more specialized in cognitive-intensive occupations. Motivated by empirical literature on the association between information and communications technology (ICT) adoption and production fragmentation, we develop a spatial equilibrium model with domestic production fragmentation to analyze the impact of a reduction in the costs of cross-city production teams—e.g., communications cost—on spatial distribution of skills and economic activities. The model generates predictions consistent with the observed empirical patterns, including more spatial segregation of skilled and unskilled workers, and occupation specialization across U.S. cities over time. In contrast to findings in the international offshoring literature, in which there are winners and losers, we find Pareto welfare gains for all agents with heterogeneous talents, together with a substantial measured labor productivity increase at the aggregate level.

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1 Introduction

One of the most revolutionary technological developments in recent decades has been the advances in transportation and communications technology. It blurs geographic boundaries, altering what teams of economic agents can do at a distance and reducing the costs of managing off-site teams. As a result, more cross-regional teams can be formed. This “geographic fragmentation” of production processes affects not only organization and hiring decisions of firms, but also workers’ occupation and location choices. There are two broad types of geographic fragmentation: one is the formation of international teams crossing national borders, commonly referred to as international offshoring; and the other is domestic teams crossing city boundaries, which we label as domestic offshoring. These two seemingly parallel issues have not received comparable attention in the literature. In contrast to the extensive research on international offshoring, domestic production fragmentation is understudied. The key difference between these two lies in the assumption on labor mobility. Individuals are immobile across international borders, whereas they are generally assumed to have free mobility across cities. Firm fragmentation domestically may therefore lead to relocation of labor and potentially redistribution of skills across different local labor markets, and have very different welfare and productivity implications.

This paper seeks to investigate how the formation of cross-city production teams, or domestic offshoring, affects spatial distribution of skills, occupations and wages. Intuitively, production of goods involves two key tasks, knowledge inputs and standardized production (e.g., Garicano, 2000; Garicano and Rossi-Hansberg, 2006). Managers, which refer to people who produce knowledge in general, tend to locate in larger cities in order to leverage the agglomeration forces offered in these locations; workers performing standardized production, on the other hand, may find it more beneficial to be in smaller cities to save costs. In another word, different cities have comparative advantages in different occupations. As a result, cities of different sizes would also specialize in different tasks associated with these occupations. With a drop in communications cost, firms would be more willing to break up their production processes, to better take advantage of the differentiated locational benefits offered in cities of different sizes. This reinforces the pattern of specialization across cities.

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1 There is a number of literature that studies the various forms of mobility cost in reality, see e.g., Enrico (2011), Baum-Snow and Pavan (2012), and Ferreira, Gyourko and Tracy (2011). This paper focuses on long-run impact of domestic offshoring, and we thus take a position that in the long run, individuals are very much mobile.

2 In this study, we use ‘firms’ and ‘production teams’ interchangeably. Cooperation of productions can happen intra- or inter-firms. For example, a furniture production team can be either an individual firm, or
Additionally, we study the consequences of this increasing city specialization on welfare, wage inequalities, aggregate productivity at both national and local city levels.

We first establish some stylized facts on the relocation of high skilled workers across cities between 1980 and 2010. We show that this trend of relocation coincides with a period of growing fragmentation of production processes, i.e., occupation relocation. Second, we develop a model that reproduces these facts. The key elements of the model are occupation sorting and location sorting, i.e., a continuum of agents with heterogeneous abilities endogenously forming production teams by taking on different roles (i.e., managers versus workers), and choosing their locations. Additionally, managers choose geographic organization of production to maximize the profits. Equilibrium conditions determine the extent of production fragmentation, distribution of skills, wages, and housing prices. Finally, the model yields estimating equations involving observable skill distribution across cities. We plan to use these equations to quantify impacts of production fragmentation and perform counterfactual welfare analyses in future work.

The most interesting theoretical findings of our paper concerns welfare impact. The paper finds that a reduction in communications cost leads to an increase in the extent of skill specialization across cities, with higher skilled workers moving to larger cities and lower skilled workers moving to smaller cities. We show that this geographic redistribution of skills necessarily benefits labors of all skill levels. In addition, there is an overall efficiency gain with a large increase in the aggregate labor productivity. The reason is twofold: one is the direct effect of communications cost reduction; the other is that the communications cost reduction facilitates spatial relocation with managers becoming more concentrated in bigger cities. Thus, productivity increases further from the additional agglomeration forces created by human capital externality.

This paper is related to several strands of literature. First, the geographic fragmentation of process in our project is similar to that in international offshoring. There is a large volume of research on international offshoring, which arises when falling transportation or communications costs motivate firms to disintegrate production and send certain jobs overseas to take advantage of comparative advantages. A consequence of this practice is growing vertical specialization in which countries increasingly specialize in one part of a good’s production process (Hummels, Ishii and Yi, 2001). Much research effort is devoted to analysis of wage inequality, in response to the offshoring of unskilled labor-intensive tasks to less
developed countries (see, e.g., Feenstra, 1998; Antras, Garicano and Rossi-Hansberg, 2006a; Grossman and Rossi-Hansberg, 2008; Robert-Nicoud, 2008). Most of the literature predicts that offshoring brings efficiency gains but enlarges wage inequality, worsening the position of unskilled workers in developed countries. This welfare implication is in sharp contrast to our model prediction that firm fragmentation benefits workers of all skill levels, resulting in Pareto improvement.

Our work is closely connected to literature on cross-city analysis of firm fragmentation. Duranton and Puga (2005) pioneers the theoretical research, for which they develop a model with homogeneous labor who are mobile across cities and sectors. The model considers an endogenous relationship between local productivity and industrial agglomeration. The paper concludes that low communications cost facilitates separation of managerial and manufacturing units in different cities. Liao (2012) extends the canonical model to include two types of workers and focuses specifically on business support services. The paper documents that low-skill support workers tend to leave large cities and migrate to rural areas, and finds that these low-skill workers are made better off as firm fragmentation allows support workers to benefit from the higher productivities in cities without bearing the high costs. Our model, however, is novel in four key dimensions. First, it is the first paper to include heterogeneous individuals with a continuum of skill distribution. Second, occupation choices are endogenous and related to the heterogeneity in skills. Third, the actual production function is generated endogenously from a production process that does not assume skill complementarities, but rather is derived from the specialization of agents in different aspects of the process — production and knowledge. Lastly, we model firm-level productivity in different cities as coming from a random probability distribution, linking manager’s own skill level, city-pair characteristics and agglomeration forces. As a result of these differences, we are able to move beyond previous contributions, and formally analyze how the process of production fragmentation determines the countrywide organization of production, the structure of rewards that support it, and most importantly, the impact on individuals’ real wage for the entire skill distribution. In addition, our model is also able to yield results consistent with a large number of urban economics literature on urban wage premium and patterns of skill premia (see e.g. Glaeser and Maré, 2001; Glaeser and Gottlieb, 2009; Davis and Dingel, 2012). These important empirical facts would not be revealed in a simpler model with only homogeneous or two types of workers.

A large number of empirical literature supports our framework and results. Manufactur-
ers often contract out specialized business services (Abraham and Taylor, 1996), and this propensity increases with city size (Ono, 2007), and particularly, those with management headquarters in large cities are more likely to contract out less important parts of the production process (Ono, 2003). Determinants of firms’ decision to geographically separate headquarters from production include scale, with larger firms more likely to engage in spatial fragmentation (Aarland et al., 2007), and proximity to production facilities (Holmes and Stevens, 2004; Henderson and Ono, 2008). In addition, this spatial specialization pattern has become more pronounced over time. Strauss-Kahn and Vives (2009) analyze that between 1996 and 2001, headquarters tend to move away from locations with relatively few other headquarters and business service producers, and towards locations with a greater presence of them. Duranton and Puga (2005) document the pattern of increasing functional specialization in the US cities, with larger cities being more specialized in management functions whereas smaller cities in production through time. Our model is able to reproduce all these empirical results.

Our model features occupation hierarchy a la Lucas (1978). Agents endogenously choose their occupations based on their innate skills. In our (benchmark) model, similar to Lucas (1978), once an agent becomes a production worker, her innate skill no longer matters; while if he chooses to be a manager, her productivity is directly linked to the skill that he is endowed with. Garicano (2000) and Garicano and Rossi-Hansberg (2006) are more sophisticated models with hierarchy. They endogenize knowledge acquisition and study more than two layers of hierarchy. Garicano (2000) is a model without agent heterogeneity in innate skills. Garicano and Rossi-Hansberg (2006) address the inequality issue with heterogeneous agents. Agents sort into different layers based on their innate skills. They show that reduction in communications cost between layers will increase the value of organization, i.e. asking others to solve problems. Inequality between layers will increase since higher layer agents will acquire more knowledge, amplifying the skill difference between layers. While we share the element of firm hierarchy with them, our paper emphasizes the spatial dimension of skill distribution which is not explored in these papers. As mentioned above, Antràs, Garicano and Rossi-Hansberg (2006b) discuss hierarchy in international offshoring context with reduction in management (communications) cost, but our paper concentrates on the within country outcome of reduction in management cost with labor mobility across cities.

Our paper is among the growing literature with models of a system of cities. Davis and Dingel (2014) incorporate Costinot and Vogel (2010) into a city system with explicit internal urban structures. While previous literature generally assumes countries’ factor endowments
exhibit log-supermodularity, they obtain this property for cities skill distributions endogenously. They show that larger cities are skill-abundant and specialize in skill-intensive industries. While agglomeration force is exogenous given in that paper, Davis and Dingel (2012) endogenize this human capital externality due to idea exchange. Because of the stronger human externality in larger cities, they show that skill premia is larger in larger cities. Our paper will not address the source of agglomeration while we think human capital externality between high skilled managers who engage in more cognitive tasks is a natural assumption, possibly coming from the force described in Davis and Dingel (2012) or Duranton and Puga (2004). Behrens, Duranton and Robert-Nicoud (2014) have a model with a system of cities as well. However, their agglomeration force is a result of standard Dixit-Stiglitz gain from variety. Agents also sort into different occupations, but they introduce two draws for each agent. One is their innate talent, the other is serendipity to separate spatial sorting ex-ante and productivity selection ex-post. They assume that after knowing her talent, agents can freely choose where to live, but agents cannot move after drawing serendipity. We have a similar assumption, after drawing idiosyncratic preference and innate skill, agents can freely choose where to live, but they cannot move after that. While all the illuminating papers above construct models with system of cities as well, we study the endogenous choice of cross-city production teams with heterogeneous agents, with explicit emphasis on production organizations. That is, the cross-city organization is a form of linkage between cities we would like to highlight.

Our model is also related to the growing literature on resource allocation and aggregate productivity. Hsieh and Klenow (2009) discuss China and India’s resource allocation is far from efficient compared to US. Moll (2014), Midrigan and Xu (2010) study capital market frictions (or financial frictions) resource misallocation. Brandt, Tombe and Zhu (2013) focuses factor market distortions in space, time and sectors in China, etc. Our study explores a new friction that limits labor relocation thus affects aggregate productivity, i.e. communications costs associated with cross-city organizations. The increase in (measured) aggregate productivity in our paper is not only directly from the reduction in communications cost, but also from the agglomeration force among the high skilled. We decompose these two channels in our analysis.

The rest of the paper is organized as follows. Section 2 presents the empirical findings. Section 3 and Section 4 introduce the model, provide theoretical analysis, and equilibrium properties. Section 5 discusses future works and concludes.
2 Stylized Facts

2.1 Data

Our analysis draws on the Census Integrated Public Use Micro Samples (IPUMS) for 1980, and the American Community Survey (ACS) for 2010. The IPUMS for 1980 include 5 percent of the US population, and the ACS samples in 2010 include 1 percent of the population. Our worker sample consists of individuals who were between age 16 and 64, and who were working in the year preceding to the survey. Residents of institutional group quarters such as prisons and psychiatric institutions are dropped along with unpaid family workers. Labor supply is measured by the product of weeks worked times usual number of hours worked per week. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight. For our empirical analysis, we also exclude workers in non-tradable services occupations, as our model only considers tradable sector.\(^4\)

The geographic unit for our study is the metropolitan statistical areas, or MSAs henceforth. Each MSA is treated as an independent economy. MSAs are defined by the US Office of Management and Budget; they consist of a large population nucleus and adjacent communities that have a high degree of social and economic integration with the core city.

2.2 Relocation of Skilled Workers

In this section, we establish the stylized facts that between 1980 and 2010, there has been relocation of high skilled workers from smaller cities to larger cities.

Change in Skill Distributions in Large v.s. Small Cities

To study how spatial redistribution of skills, we first categorize cities into two groups, based on their population in 1980, and investigate how employment has changed for the period of 1980 to 2010 across occupations of different skill levels. Following Acemoglu and Autor (2011), we rank skill levels of different occupations, approximated by the mean log wage of workers in each occupation in 1980.\(^5\)

\(^4\)Autor and Dorn (2013) provides an in-depth analysis on the growth in employment and wage for non-tradable services workers. See Appendix A.1 for the list of non-tradable services workers.

\(^5\)Examples of occupations in the lower wage-rank distribution (1-20\%tile) include child care workers, waiters and waitresses, housekeepers, hotel clerks, kitchen workers, and bartenders. Examples of occupations
Figure 1 calculates the change between 1980 and 2010 in the share of employment accounted for by 318 detailed occupations. The vertical axis plots log changes in employment shares. The horizontal axis represents the 1980 occupation skill percentile rank, measured as the employment weighted percentile rank of an occupation’s mean log wage in the Census IPUMS 1980 five-percent extract. As shown in Figure 1, larger cities experience a larger increase in employment share of high-skilled workers and a larger decrease the employment share of lower-skilled workers relative to smaller cities. This provides evidence suggesting that there had been relocation of more skilled workers from smaller cities to larger cities between 1980 and 2010.

The analysis reveals the pattern of labor movement for a continuous distribution of skills between the group of large cities and the group of small cities. We next carry out a complementary exercise to study the relationship between skill distribution and city sizes.

**Change in Abstract Employment Share with respect to City Sizes**

To ascertain that there is indeed a spatial dimension in the evolution of skill distributions, we take a closer look at the correlation between changes in the skill content of a city and the population. To do so, we construct a summary statistic that measures relative share of high-skilled workers, following Autor, Levy and Murnane (2003) and Autor and Dorn (2013). This methodology first considers the skill content of each occupation and classifies all census occupations as either *abstract task-intensive* or *non-abstract task intensive*. We then compute the share of abstract task-intensive employment for each MSA $c$ in year $t$, i.e. $ASH_{ct}$. The $ASH_{ct}$ summarizes the aggregate skill level for city $c$ in year $t$.

Figure 2 relates the shares of abstract-intensive employment in 1980 and 2010 to metropolitan area populations. The left panel plots this share in each city against the city population in 1980 and 2010; the right panel plots change in the share of abstract-intensive employment against the city initial population. From 1980 to 2010, larger cities experience a larger

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6For this 30-year period, we estimate that large cities undergo a 5% of the employment share of lower-skilled workers, and a 10% increase in the employment share of high-skilled workers. The corresponding changes in small cities are 3% and 4% respectively.

7Appendix A.2 provides more details on the construction of the $ASH$ index.
increase in the share of abstract task intensive employments.\textsuperscript{8} This is consistent with the results above, suggesting that there is increasing specialization of skills across cities.

**Change in Share of College Educated with respect to City Sizes**

Analyses above show that the larger cities experience greater relative inflow of high skilled workers, compared to smaller cities. We confirm this empirical observation, using education as a proxy to measure skill levels. Figure 3 relates shares of employment with college and above education in 1980 and 2010 and metropolitan area populations. The left panel plots this share in each city against the city population in 1980 and 2010; the right panel plots change in the share of college educated employment against the city initial population. As shown, larger cities are associated with greater increase in the share of employment with college and above education, consistent with the analysis using task content of occupations.\textsuperscript{9}

**Specialization Measure**

Following Duranton and Puga (2005), we compute a measure for the pattern of specialization of high-skilled occupations (or managers) across cities of different sizes. We first calculate the ratio of managers to workers (i.e. number of managers per low-skilled worker) in cities of each size class.

$$\mu_c = \frac{N_c^{manager}}{N_c - N_c^{manager}},$$

where $N_c$ and $N_c^{manager}$ denote overall employment in city $c$ and employment in managers in city $c$ respectively. The measure is computed as the percentage difference between this ratio and the corresponding ratio for the entire country.

We then compare the changes in this ratio across city sizes. From Table 1, we can see that in both 1980 and 2010, there is a clear ranking by city size, i.e. larger cities house relatively more workers engaging in high-skilled tasks. For example, in 1980, the largest metro areas had 10.9% more manager-per-worker ratio than the national average. For MSAs with a current population between 2 to 3 million, the figure was 3.1% below the national average. At the other extreme, MSAs with less than 500,000 population had 9.9% fewer manager per worker than the national average.

\textsuperscript{8}OLS regression: $\Delta ASH_{c,2010-1980} = \beta_0 + \beta_1 \cdot \ln(\text{Pop}_{c,1980}) + \epsilon_{c,2010-1980}$. Estimate for $\beta_1$ is 0.0318 with standard error 0.0008.

\textsuperscript{9}OLS regression: $\Delta CollegeEdu_{c,2010-1980} = \beta_0 + \beta_1 \cdot \ln(\text{Pop}_{c,1980}) + \epsilon_{c,2010-1980}$. Estimate for $\beta_1$ is 0.0256 with standard error 0.0105.
More importantly, between 1980 and 2010, larger cities had become even more specialized in high-skilled tasks whereas smaller cities had become more specialized in low-skilled tasks. This pattern is significant. In 2010, metro areas with more than 3mil population and between 2 to 3mil population had 13.3% and 1.9% more managers than national average, respectively. On the other hand, the relative number of managers in the smallest urban areas saw a reduction, to 19.3% below the national level.\footnote{Similar patterns are observed when using overall employment and alternative definitions based on Census classification of Production, Managerial and Technical occupations}

## 2.3 Patterns of Production Process Fragmentation

We next establish patterns of increasing production fragmentation. While this is a well documented trend in literature (see, e.g., Kim, 1999; Duranton and Puga, 2005; Rossi-Hansberg, Sarte and Owens, 2009), we provide additional evidence in this section showing the greater spatial segregation of high and low skilled workers for the period of 1980 and 2010. In our analysis, managers are defined as those engaging in abstract task-intensive occupations.\footnote{Our results are consistent when we use alternative definition based on the Census occupations, in which high skilled workers are defined as those in Professional, Managerial or Technical occupations (based on 3-digit occ1990 codes).}

### Spatial Concentration: Isard Index

We first use Isard index to measure the spatial concentration of managers (Krugman, 1991). This index measures spatial concentration based on the absolute distance between the actual and benchmark employment distribution. In our analysis, \( I \) denotes concentration of managers based on the distance between the local share of managers and the local employment share for all occupations. If occupations are evenly distributed across all cities based on overall employment share, the measure would be 0; whereas if all managers are concentrated in one city, the measure would be 1. The original measurement is given by:

\[
I = \frac{1}{2} \sum_{c=1}^{C} \left| \frac{N_{c}^{\text{manager}}}{N_{\text{manager}}} - \frac{N_{c}}{N} \right|,
\]

where \( N_{c} \) and \( N_{c}^{\text{manager}} \) denote overall employment in city \( c \) and employment in managers in city \( c \) respectively.
For the period of 1980 to 2010, it is possible that different cities had also undergone shifts in their sectoral composition. For example, more skill intensive sectors such as aerospace engineering may become more concentrated in larger cities compared to sectors that are less skill intensive, which may also generate a higher concentration of high-skilled occupations in the larger cities. To account for such shifts in sectoral composition across cities, we adjust the above measure to control for any change in spatial concentration of high-skilled employment due to this sectoral composition change.

\[
\tilde{I} = \frac{1}{S} \sum_{s=1}^{S} \left[ \frac{1}{2} \sum_{c=1}^{C} \left| \frac{N_{cs}^{manager}}{N_s^{manager}} - \frac{N_{cs}}{N_s} \right| \right]
\]

where \( S \) denote the total number of industrial sectors in the economy.

Using the improved measure, we find that the Isard index increased from 0.0953 to 0.130 from 1980 to 2010, indicating an increase in spatial concentration of managers.

**Segregation of PMT: Kremer & Maskin Index**

Next, we consider another measure developed by Kremer and Maskin (1996), and subsequently used widely to measure degree of segregation (e.g., Dunne et al., 2002; Liao, 2012).

\[
\rho = \frac{\sum_c N_c \cdot (\pi_c - \pi)^2}{N \cdot \pi \cdot (1 - \pi)}
\]

where \( \pi_c = N_{c}^{manager}/N_c \), or share of managers in a city \( c \).

This index measures how correlated the employment share of different occupations are within a city. It is constructed as the ratio of the variance of share of managers across cities to the variance of an agent’s occupation status (i.e. manager vs. worker) of the total population.\(^{12}\) When \( \rho = 0 \), there is no segregation, i.e. managers and workers are always in the same cities; when \( \rho = 1 \), there is complete spatial segregation of managers and workers.

We again adjust the measure to account for any change in \( \rho \) due to shifts in sectoral composition across cities, using

\[
\hat{\rho} = \frac{1}{S} \sum_{s} \left[ \frac{\sum_c N_{cs} \cdot (\pi_{cs} - \pi_s)^2}{N_s \cdot \pi_s \cdot (1 - \pi_s)} \right] .
\]

\(^{12}\)This is equivalent to the \( R^2 \) value of a regression of share of managers on a series of city dummies.
Kremer and Maskin (1996) also construct a confidence interval for the segregation index under the assumption that the sampling errors in the estimates of the variance of employments within and between the cities are independent. 95% confidence interval of the index of segregation is:

\[
\frac{F(N - J, J - 1)_{0.025}}{F(N - J, J - 1)_{0.975}} \leq \hat{\rho} \leq \frac{F(N - J, J - 1)_{0.975}}{F(N - J, J - 1)_{0.025}} + \frac{1 - \rho}{\rho},
\]

where \( J = C + S \).

As shown in Table 2, \( \rho \) had more than tripled from 1980 to 2010, and the increase was also statistically significant. This indicates that managers and workers had become increasingly more spatially segregated.

3 The Model

In this section, we develop a spatial equilibrium model that generates theoretical predictions consistent with the set of empirical facts documented in the previous section.

3.1 Set-up

There are in total ex ante identical \( N \) cities. In the baseline model, we assume that cities are endowed with a fixed amount of housing supply, owned by absentee landlords. There is a continuum of individuals of mass \( L \) in the economy, with ability \( z \) distributed with p.d.f. \( \mu(z) \). An agent first observes her skill and selects her occupation as either a manager, or a production worker. The agent then chooses where to live. Upon her moving to a city, a manager draws a productivity from all \( N \) cities. Based on the productivity draw, a manager sets up a firm, choosing where the production takes place and how many workers to hire. In our model, production workers have to live in the city where production happens, but not necessarily for managers. Figure 4 is a schematic illustration of the model structure. We go through each step below in detail.

In this model, agents have two exogenous draws — the skill draw and the productivity draw. The skill draw generates spatial sorting of agents, while the productivity draws allow cities to have production teams of differentiated productivities. Empirically, there are frictions to mobility. Following conventional literature (see e.g., Behrens, Duranton and
Robert-Nicoud, 2014), we assume free mobility before productivity draw occurs and prohibitive mobility costs afterwards. Allowing individuals to move after the productivity draw would result in perfect sorting of productivities across cities, which is clearly counterfactual. On the other hand, our assumption allows us to model mobility frictions in a parsimonious and tractable way.

3.2 Preferences

Individuals consume two goods: a homogeneous tradable good, and housing. The total supply of each city $n$ is fixed at $H$. The utility function is in Cobb-Douglas form:

$$U(c, h) = \alpha^{-\alpha}(1 - \alpha)^{-(1 - \alpha)}c^{\alpha}h^{1 - \alpha},$$

where $c$ is the consumption of tradable good and $h$ is the consumption of housing.

The indirect utility function, therefore, for a consumer with income $w_n$ facing rent $p_n$ in city $n$ is:

$$V(p_n, w_n) = \frac{w_n}{p_n^{1 - \alpha}}. \quad (1)$$

Note that in equilibrium, housing rents are given by:

$$p_n = \frac{(1 - \alpha)W_n}{H}, \quad (2)$$

where $W_n$ is the total income in city $n$.

3.3 Production and Skills

Individuals, with skills $z$ distributed with p.d.f. $\mu(z)$, first select into their occupations. If an agent chooses to be a production worker, her productivity is assumed to be at a fixed homogeneous level $\bar{z}$. Therefore, within a city, all production workers will receive the same wage; across cities, production workers receive the same indirect utility, i.e.

$$V_n^w = V_{n'}^w = \bar{\nu} \forall \ n, \ n',$$

13For now, we assume that housing supplies are identical across cities.
Managers differ in their productivities, which are monotonically related to their skill level $z$. Thus, a manager’s income (in expectation) is monotonic related to $z$. Agents decide their occupations before they choose where to live. Managers who live in city $n$ can hire workers in city $c$ with the following technology:

$$y_{nc} = a_{nc}l^\beta.$$  

This production technology follows Lucas (1978). It involves two elements: first, variable skills $a_{nc}$, which can be thought of as “manager’s productivity”; second, $\beta < 1$ is an element of diminishing returns to scale, or the “span of control”. In this setup, each “firm” is comprised of a single manager and $l$ homogeneous employees.

Managers are the residual claimants of the firms’ profit. Hence, managers’ income is the firm profit:

$$\pi_{nc} = \frac{a_{nc}l^\beta}{w_c} - w_c l,$$

where $\tau_{nc}$ is an iceberg cost which reflects the cost of managing workers in different cities. We assume that $\tau_{nn} = 1$ and $\tau_{nc} \geq 1$.

Given $a_{nc}$, a manager chooses the size of her production team, $l$, to maximize her income. The first-order condition is given by:

$$l^* = \left(\frac{\beta a_{nc}}{\tau_{nc} w_c}\right)^{\frac{1}{1-\beta}}.$$  

(4)

Notice that a more productive manager, i.e., high $a_{nc}$, manages a larger production team.

A manager living in city $n$ with a production team in city $c$ has an income of:

$$\pi_{nc}^* = \beta^{\frac{1}{1-\beta}}(1 - \beta)\left(\frac{a_{nc}}{\tau_{nc} w_c^\beta}\right)^{\frac{1}{1-\beta}}.$$  

From this equation, it is straightforward to see that the iceberg management cost $\tau_{nc}$ lowers managers’ income.

Managers’ productivity, $a_{nc}$, has two components: one fixed component, which is related to the manager’s innate skill and the city she lives in, denoted by $f(Z_n, z)$, and the other is
a random draw, denoted by \( \bar{a}_{nc} \). The two components are assumed to enter the manager’s productivity function multiplicatively:

\[
a_{nc} = f(Z_n, z)\bar{a}_{nc}.
\]

Here \( \bar{a}_{nc} \) does not depend on the manager’s innate skill \( z \) or the city’s aggregate skill \( Z_n \).

### 3.4 Production Location Choice

A manager who lives in city \( n \) draws her productivity \( \bar{a}_{nc} \) from \( N \) cities. The draws follow Fréchet distributions, i.i.d. across individuals and cities:

\[
Pr(A_{nc} \leq \bar{a}_{nc}) = e^{-\bar{a}_{nc}^{\theta}}.
\]

Note that support of the above distribution is \( \bar{a} \geq 0 \).

Consider a manager who lives in city \( n \). She would choose a city \( c \), which would give her the largest value of \( \frac{\bar{a}_{nc}}{\tau_{nc}w_c^\beta} \), to locate the production team. Given distribution \( \bar{a}_{nc} \), we derive the following “offshoring gravity equation”, similar in both concept and form to the traditional gravity equation in international trade.

**Proposition 1** The probability of a manager who lives in city \( n \) and locates production in city \( c \) is

\[
\frac{T_{nc}(\tau_{nc}w_c^\beta)^{-\theta}}{\Phi_n},
\]

where

\[
\Phi_n = \sum_k T_{nk}(\tau_{nk}w_k^\beta)^{-\theta}.
\]

Notice that the summation of all probabilities is 1.

**Proof.** Denote \( X_{nc} = \frac{A_{nc}}{\tau_{nc}w_c^\beta} \), then

\[
G_{nc}(x) = Pr(X_{nc} \leq x) = Pr(A_{nc} \leq \tau_{nc}w_c^\beta x) = e^{-T_{nc}(\tau_{nc}w_c^\beta)^{-\theta}x^{-\theta}}.
\]

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\(^{14}\)This is observationally equivalent if we use a joint Fréchet distribution. See Eaton and Kortum (2002), footnote 14, for a discussion.
Distribution of $X$ that a city $n$ actually adopts is:

$$G_n(x) = \Pi_{c=1}^{N} G_{nc}(x) = e^{-\Phi_n x^{-\beta}}.$$  

Probability that city $c$ provides highest $x$ to $n$ is:

$$Pr[X_{nc} \geq \max \{x_{ns} : s \neq c\}] = \int_0^\infty \prod_{s \neq c} [G_{ns}(x)] dG_{nc}(x) = \frac{T_{nc}(\tau_{nc} u_n^\beta)^{-\theta}}{\Phi_n}.$$  

Based on this proposition, it is easy to see that a technological development that drives down cross-city management cost, $\tau_{nc}$, increases the possibility of cross-city group, holding everything else equal. By WLLN, the production fragmentation gravity equation also gives the fraction of managers living in city $n$, locating her production team in city $c$.

### 3.5 Manager’s living location choice

Given distribution of productivity draw, we also derive the distribution for managers’ income.

**Proposition 2** The income of a manager who is endowed with skill $z$ and lives in city $n$ follows the following Fréchet distribution with c.d.f.

$$Pr(\pi_{nz} \leq k) = e^{-f(Z_n, z)^{\beta} \Phi_n \beta (1-\beta) k^{-\theta} k^{\theta(1-\beta)}}.$$  

**Proof.**

$$Pr(\pi_{nz} \leq k) = Pr \left[ \beta^{\frac{\beta}{1-\beta}} (1-\beta) f(Z_n, z)^{\frac{1}{1-\beta}} \max_c \left\{ \left( \frac{A_{nc}}{\tau_{nc} w_c^\beta} \right)^{\frac{1}{1-\beta}} \right\} \leq k \right]$$

$$= Pr \left[ \max_c A_{nc} \leq \beta^{\frac{\beta}{1-\beta}} (1-\beta)^{1-\beta} \tau_{nc} w_c^\beta k^{1-\beta} / f(Z_n, z) \right]$$

$$= e^{-f(Z_n, z)^{\beta} \Phi_n \beta (1-\beta) k^{-\theta} k^{\theta(1-\beta)}}.$$  

By properties of Fréchet distributions, the expected income of a manager ($z$) living in city
\[ n \text{ is thus:} \]
\[ E[\pi_{nz}] = \zeta [f(Z_n, z)^\theta \Phi_n]^{\frac{1}{\theta}} , \]

where \( \zeta \) is a constant:
\[ \zeta = \theta \beta - \frac{\beta}{1 - \beta} \int_0^{+\infty} e^{-x - \theta(1 - \beta)x - \theta(1 - \beta)} dx. \]

Recall that each manager first chooses her location to live and then determines the location to hire workers to produce. A manager will choose her living location to maximize her indirect utility. Denote by \( \Psi_{nz} \), a manager’s expected utility function is given by:
\[ \Psi_{nz} = \log \left\{ \frac{E[\pi_{nz}]}{p_n} \right\} = \text{const} + \frac{1}{1 - \beta} \log f(Z_n, z) + \frac{1}{\theta(1 - \beta)} \log \Phi_n - \log p_n. \]

A manager’s problem is therefore to maximize \( \Psi_{nz} \).

3.6 Occupation choice

Given \( z \), an agent’s occupation choice is endogenously determined. For efficient allocations, only the most skilled take up managerial positions. This is directly related to the occupation sorting results from Lucas (1978).

Lemma 3 There will be a cutoff \( z^* \) such that all agents with \( z < z^* \) become production workers, while the remaining agents become managers.

Proof. Suppose not. \( z_1 < z_2 \) but \( z_1 \) chooses to be a manager while \( z_2 \) chooses to be a production worker. Since a manager’s indirect utility is monotonically increasing in \( z \), we have
\[ v^m(z_1) \leq v^m(z_2) \]

But \( z_1 \)’s occupation choice implies \( v^m(z_1) \geq \bar{v} \) then
\[ v^m(z_2) > v^m(z_1) \geq \bar{v}, \]

i.e. \( z_2 \) will also choose to be a manager, a contradiction. □
3.7 Equilibrium conditions

An equilibrium for a total population of $L$ with skill distribution $\mu(z)$ in a set of cities, \( \{n\}_{n=1}^{N} \), is a set of housing prices \( \{p_n\} \) and populations $\mu(z,n)$, such that:

1. Individuals maximize Equation (1) by their choices of occupation, living location, and (for managers) size of production team and production location;

2. Housing market clear, i.e. Equation (2) holds.

3. Labor market clears, i.e. Equations (5), (6), (7) hold.

\[
\mu(z) = \sum_n \mu(z,n) \quad \forall z \quad (5)
\]

\[
L^w_n = L \int_0^{z^*} \mu(z,n)dz \quad \forall c \quad (6)
\]

\[
L^m_n = L \int_{z^*}^{\infty} \mu(z,n)dz \quad (7)
\]

By Walras’ Law, tradable goods market clears under these conditions.

To fully analyze the characteristics of the equilibrium, we make the following assumptions for the remaining parts of the paper:

**Assumption 1:**
The aggregate city-level skill $Z_n$ is given by:

\[
Z_n = J(\int_{z^*}^{\infty} j(z)\mu(z,n)dz), \quad (8)
\]

where $\mu(z,n)$ represent the distribution of managers with skill $z$ in city $n$; $J(\cdot)$ is a positive, strictly increasing function, and $j(\cdot)$ is a positive, non-decreasing function. $Z_n$ incorporates both the size of the manager population and their average skill level in a city $n$.\(^{15}\)

**Assumption 2:**
The fixed term in managers’ productivity, $f(Z_n, z)$, are twice-differentiable, and log-supermodular in $(Z_n, z)$, i.e.

\[
\frac{\partial^2 \log f(Z_n, z)}{\partial Z_n \partial z} \geq 0,
\]

\(^{15}\)Form of $Z_n$ adopts the city-level aggregate skill defined in Davis and Dingel (2014).
or

\[
\frac{f(Z_1, z_1)}{f(Z_1, z_2)} > \frac{f(Z_2, z_1)}{f(Z_2, z_2)}, \quad \forall Z_1 > Z_2, z_1 > z_2.
\]

4 Spatial Equilibria

4.1 Homogeneous Equilibrium

Many spatial models featuring endogenous agglomeration forces have two classes of equilibria: equilibria in which all cities are identical; and equilibria with heterogeneous cities. So far, we have assumed that city fundamentals are symmetric. Under this assumption, our model also generates two types of equilibria: homogeneous vs. heterogeneous.

Homogeneous equilibrium in our model is defined as cities with the same number of managers and the same city aggregate skill level, i.e. \( L_{m}^{n} = L_{m}^{n'} \) and \( Z_{n} = Z_{n'} \) \( \forall n, n' \).16 This implies that \( w_{n} = w_{n'} \), \( p_{n} = p_{n'} \) and \( L_{w}^{n} = L_{w}^{n} \). In another word, all cities are identical. This type of equilibrium is not only empirically irrelevant, but also not stable, as stated in the following proposition.

**Proposition 4** Assuming all cities have the same fundamentals, and that \( \tau_{nc} = \tau \) and \( T_{nc} = T \), homogeneous cities cannot exist in a locally stable equilibrium.

We provide the proof for this proposition in Appendix A.3. Intuitively, if we move a small mass of managers with high skills from one city to another, city aggregate skill level increases, drawing more managers into the city. For the remaining discussions, we focus on the heterogeneous equilibria.

4.2 Cities of Heterogeneous Sizes

We next consider a system of heterogeneous cities. Given the log-supermodularity assumption for \( f(z, Z_{n}) \), we have the following results.

**Proposition 5** There is spatial sorting of managers in which higher skilled managers live in cities with higher aggregate skills.

---

16We do not distinguish homogeneous and heterogeneous equilibria using city population sizes as in our model, total population in a city depends on a firm’s production fragmentation decision.
Proof. Spatial sorting states that for all \( z_2 > z_1 > z^* \), if \( \mu(z_2, c_2) > 0 \) and \( \mu(z_1, c_1) > 0 \), then \( Z_2 \geq Z_1 \).

\[
\mu(z_2, c_2) > 0 \implies \forall c, \quad \frac{1}{1-\beta} \log f(Z_2, z_2) + \frac{1}{\theta(1-\beta)} \log \Phi_2 - (1-\alpha) \log p_2 \geq 0
\]

\[
\frac{1}{1-\beta} \log f(Z_c, z_2) + \frac{1}{\theta(1-\beta)} \log \Phi_c - (1-\alpha) \log p_c
\]

\[
\mu(z_1, c_1) > 0 \implies \forall c, \quad \frac{1}{1-\beta} \log f(Z_1, z_1) + \frac{1}{\theta(1-\beta)} \log \Phi_1 - (1-\alpha) \log p_1 \geq 0
\]

Specifically

\[
\frac{1}{1-\beta} \log f(Z_2, z_2) + \frac{1}{\theta(1-\beta)} \log \Phi_2 - (1-\alpha) \log p_2 \geq 0
\]

\[
\frac{1}{1-\beta} \log f(Z_1, z_2) + \frac{1}{\theta(1-\beta)} \log \Phi_1 - (1-\alpha) \log p_1 \geq 0
\]

and

\[
\frac{1}{1-\beta} \log f(Z_1, z_1) + \frac{1}{\theta(1-\beta)} \log \Phi_1 - (1-\alpha) \log p_1 \geq 0
\]

\[
\frac{1}{1-\beta} \log f(Z_2, z_1) + \frac{1}{\theta(1-\beta)} \log \Phi_2 - (1-\alpha) \log p_2 \geq 0
\]

\[
\implies \log f(z_2, Z_2) + \log f(z_1, Z_1) \geq \log f(z_1, Z_2) + \log f(z_2, Z_1)
\]

Given the log-supermodularity of \( f(\cdot, \cdot) \), it must be that \( Z_2 \geq Z_1 \). 

Due to the spatial sorting of managers, managers with varying skill levels will choose to locate in cities with different levels of \( Z_n \), with the most skilled managers locating in the city with the highest level of \( Z_n \). Label cities in order of the value of their aggregate city-level skill so that \( Z_1 = \min_{n=1,...,N} Z_n \). Indifference between managers and production workers implies that:

\[
w_1 = E(\pi_1(z^*)) = \zeta f(Z_1, z^*) \frac{1}{1-\beta} \Phi_1^{\frac{1}{\beta-1}}.
\]

This states that in the smallest city, workers must earn the same wage as the income of the
lowest-skilled managers, i.e., those with skill level $z^*$. Label $\bar{z}_n$ as the highest skill among all managers living in city $n$. We have $\Psi_n(\bar{z}_n) = \Psi_{n+1}(\bar{z}_n)$, i.e., the boundary manager must be indifferent between the two cities. This implies:

$$
\frac{1}{1-\beta} \log f(Z_n, \bar{z}_n) + \frac{1}{\theta(1-\beta)} \log \Phi_n - (1-\alpha) \log p_n =
$$

$$
\frac{1}{1-\beta} \log f(Z_{n+1}, \bar{z}_n) + \frac{1}{\theta(1-\beta)} \log \Phi_{n+1} - (1-\alpha) \log p_{n+1}
$$

(10)

Given prices $\{p_n\}, \{w_n\}$, managers’ living locations are determined by the indifference conditions in Equations (9) and (10). To pin down $2N$ prices $\{p_n\}, \{w_n\}$, we have $N-1$ indifference conditions for workers by Equation (3), $N$ housing prices by Equation (2), and one labor market clearing condition in Equation (11).\(^{17}\)

$$
\frac{1}{1-\beta} \log f(Z_n, z) + \frac{1}{\theta(1-\beta)} \log \Phi_n - (1-\alpha) \log p_n =
$$

(11)

4.2.1 A Two-City Simulation

To illustrate the key results from our model, we consider a simple two-city case. Without loss, assume that City 2 is more skill abundant, i.e. $Z_2 > Z_1$. Given the spatial sorting results, skill levels for managers in City 1 are in $[z^*, \bar{z}]$, and managers in City 2 are in $[\bar{z}, \infty]$.\(^{18}\)

Our model does not yield closed-form equilibrium conditions; so we rely on numerical simulations to determine key equilibrium outcomes. Before we present the predictions, we illustrate that our model is able to produce results consistent with well-established facts about cities.

Figure 5 shows the nominal income and utility outcomes for a particular parameterization of our model in a two-city equilibrium. Agent’s skill, indexed by $z$, appears on the horizontal axis. We assume for the numerical simulation that skills are uniformly distributed. Since the spatial allocation of production workers ($z < z^*$) is indeterminate due to indifference condition, we order them by ability only for ease of illustration. Managers ($z > z^*$) are sorted according to skill because this maximizes their utility. $\bar{z}$ is the skill of the manager who is indifferent between the two cities.

\(^{17}\)See Appendix A.4 for details on derivation of demand for production workers.

\(^{18}\)Equilibrium conditions for the two-city model are specified in Appendix A.5.
The nominal incomes of both workers and managers are higher in the more skill abundant city. This matches the well-established empirical literature on the urban wage premium (e.g., Glaeser and Maré, 2001 and Glaeser and Gottlieb, 2009). For workers, the higher nominal wages in City 2 may be thought of as a compensation for the higher housing prices there, so that their utility is kept constant across cities. Managers’ incomes are higher in City 2 due to three reasons. First, there is a composition effect. Given the spatial sorting of skills among managers, those in the more skill-abundant cities have higher skills that generate higher income in any location. Second, there is an agglomeration externality. Since more skill-abundant cities provide greater human capital externalities due to agglomeration effects, managers in City 2 yield larger productivity gains and thus higher nominal incomes. Third, there is a compensation effect. Managers who are indifferent between two cities must have a wage gap that exactly matches the gap in housing prices between those two cities.

Figure 6 shows the pattern of skill premia. It compares the incomes of managers and workers by placing the wage schedules on a common horizontal axis. The ratio of the wage schedules gives the skill premium of each manager relative to the workers in the same city. The skill premia are higher in the more skill-abundant city, matching the novel findings documented in Davis and Dingel (2012). Skill premia are higher in City 2 due to the combination of composition and agglomeration effects. The differences in inframarginal managers’ skills and the differences in the productivity gain arising from agglomeration externalities are greater than the compensation effect that lowers the skill premium. Hence, more skill-abundant cities exhibit higher observed skill premia.

4.2.2 Impacts of increasing production fragmentation

We next illustrate key implications arising from a drop in cross-city management costs, e.g., through an improvement in communications efficiency. As $\tau$ decreases, firms are more willing to break up their production processes. As illustrated in Figure 7, this trend decreases $\bar{z}$, indicating that the most skilled managers in City 1 move to City 2 as communications costs drop. Furthermore, consistent with the empirical observations presented in Section 2, as $\tau$ decreases, managers relocate from City 1 to City 2; and workers relocate from City 2 to City 1, as illustrated in Figure 8.

We now explore the welfare consequences as $\tau$ decreases. Recall that in the standard inter-
national offshoring models, a decrease in communications cost results in an overall efficiency gain but the gain is not shared among all agents. Consistent with international offshoring models, our model generates overall efficiency gain due to the greater agglomeration externalities as cities become more specialized, as shown in Figure 9.

Crucially, our model of domestic offshoring generates very different results on the distribution of the overall efficiency gain compared to the international offshoring context. As shown in Figure 10, utilities for workers in both cities increase as $\tau$ decreases. Figure 11 illustrates that managers’ utilities also increase across all skill levels. The increase in managers’ utilities is larger for managers with higher skill levels, and also for managers living in the more skill-abundant city. These two results show that as cities get more specialized due to domestic production fragmentation, there is a Pareto improvement for all agents.

In addition, Figure 12 shows that housing prices decreases in City 1 and increases in City 2 as cities become more specialized due to domestic production fragmentation. As $\tau$ decreases, the total income in less skill abundant cities decrease while that in the more skill abundant ones increase. As an agent’s utility is given by $\frac{w_n p_n}{p_n}$, this implies that the real wage inequalities are smaller than the nominal wage inequalities across cities, as $\tau$ decreases.

5 Conclusion

In conclusion, this paper documents empirical facts on the changing spatial distribution of U.S. labor force. During 1980 and 2010, there has been relocation of skilled workers and occupations across the US cities. Big cities attract more skilled and become more specialized in abstract intensive occupations. This trend coincides with the growing spatial segregation of managers and production workers. Based on these facts, we develop a model of production fragmentation in a system-of-cities setting with heterogeneous agents. Our model differentiates from other literature in similar system-of-cities setting given our explicit emphasis on firms’ organization structure, and cross-city production team formations. The model reveals the role of falling communications cost in shaping firms’ production fragmentation decisions and generates novel predictions on skill relocation, wage changes and welfare consequences across cities. Future research should focus on documenting direct empirical evidence on the impact of falling communications cost on domestic production fragmentations.
References


Figures and Tables

Figures

Figure 1: Change in Employment Share by Occupational Skill Rank: 1980 - 2010

Source: Census IPUMS 5 percent samples for year 1980 and Census American Community Survey (1 percent) sample for 2010. All occupation in these samples refer to prior year’s employment. The figure plots log changes in employment shares by 1980 occupation skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations) where skill percentiles are measured as the employment-weighted percentile rank of an occupation’s mean log wage in the Census IPUMS 1980 5 percent extract.
Figure 2: Change in Abstract Employment Share with respect to City Sizes

Source: Census IPUMS 5 percent samples for year 1980 and Census American Community Survey (1 percent) sample for 2010.

Figure 3: Share of Employment with College Education vs. City Sizes

Source: Census IPUMS 5 percent samples for year 1980 and Census American Community Survey (1 percent) sample for 2010.
Figure 4: Schematic illustration of the model structure

Figure 5: Two-City Equilibrium: Wages and Utility
Note: $z \sim U(0,1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1, \tau = 1$
Figure 6: Two-City Equilibrium: Skill Premium
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1, \tau = 1$

Figure 7: Two-City Equilibrium: Skill Redistribution
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1$
Figure 8: Two-City Equilibrium: Labor Relocation
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1$

Figure 9: Two-City Equilibrium: Aggregate Labor Productivity
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1$
Figure 10: Two-City Equilibrium: Utility of Workers
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1$

Figure 11: Two-City Equilibrium: Utility of Managers
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1$
Figure 12: Two-City Equilibrium: Housing Prices
Note: $z \sim U(0, 1), \alpha = 0.75, \beta = 0.5, \theta = 6, L = 2, H = 1$
### Tables

<table>
<thead>
<tr>
<th>Local Pop</th>
<th>Management against production (%)</th>
<th>1980</th>
<th>2010</th>
</tr>
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<tr>
<td>Less than 500,000</td>
<td>-9.9</td>
<td>-19.3</td>
<td></td>
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<tr>
<td>500,000-1,000,000</td>
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<td>-13.7</td>
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<td>Greater than 3,000,000</td>
<td>+10.9</td>
<td>+13.3</td>
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Table 1: Increasing Specialization of US cities

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<tr>
<th>Year</th>
<th>$\hat{\rho}$</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>0.0088</td>
<td>(0.0084 0.0090)</td>
</tr>
<tr>
<td>2010</td>
<td>0.0286</td>
<td>(0.0277 0.0295)</td>
</tr>
</tbody>
</table>

Table 2: Segregation Index in 1980 and 2010
A Appendix

A.1 List of Non-Tradable Services Occupations

- Supervisors of guards
- Fire fighting, prevention, and inspection
- Police, detectives, and private investigators
- Other law enforcement: sheriffs, bailiffs, correctional institution officers
- Crossing guards and bridge tenders
- Guards, watchmen, doorkeepers
- Supervisors of food prep and service
- Bartenders
- Waiter/waitress
- Cooks, variously defined
- Food counter and fountain workers
- Kitchen workers
- Waiter's assistant
- Misc food prep workers
- Supervisors of cleaning and building service
- Supervisors of landscaping, lawn service and groundskeeping
- Gardeners and groundskeepers
- Janitors
- Elevator operators
- Pest control occupations
• Gardeners and groundskeepers
• Housekeepers, maids, butlers, stewards, and lodging quarters cleaners
• Private household cleaners and servants
• Laundry and dry cleaning workers
• Dental assistants
• Health aides, orderlies, and attendants
• Health and nursing aides
• Barbers
• Hairdressers and cosmetologists
• Recreation facility attendants
• Guides
• Ushers
• Public transportation attendants and inspectors
• Baggage porters
• Recreation and fitness workers
• Child care workers

### A.2 Definition of high-skilled abstract task-intensive occupations

To ascertain that there is indeed a spatial dimension in the evolution of skill distributions, we take a closer look at the correlation between changes in the share of higher skilled occupations and the size of cities. To do so, we need to construct a summary statistic for the relative share of high-skilled workers. Autor, Levy and Murnane (2003) (ALM henceforth) show that occupations intensive in abstract creative, problem solving and coordination tasks performed by highly-educated workers such as professionals, managers and technical personnel are in the right most tail of the occupation skill and wage distribution.
We hence construct our summary index of abstract task-intensive activities within MSAs. We measure abstract task-intensive activities using the occupational composition of employment. Following ALM, we merge job task requirements from the fourth edition of the US Department of Labor’s Dictionary of Occupational Titles (DOT) (US Department of Labor 1977) to their corresponding Census occupation classifications to measure abstract, routine and manual task content by occupation.\(^{20}\) While our theoretical model assumes that workers supply either abstract, routine or manual tasks, the DOT permits an occupation to comprise multiple tasks at different levels of intensity. We combine these measures to create a summary measure of routine task-intensity \(ATI\) by occupation, calculated as

\[
ATI_k = \ln(T_{A,k,1980}) - \ln(T_{M,k,1980}) - \ln(T_{R,k,1980})
\]

where \(T_{A,k,1980}, T_{M,k,1980}, T_{R,k,1980}\) are, respectively, the abstract, manual and routine in each occupation in \(k\) in 1980. This measure is rising in the importance of abstract tasks in each occupation and declining in the importance of manual and routine tasks. The intensity of both abstract and manual task activities is roughly monotone in occupational skill while the intensity of routine task activities is highest in the middle of the skill distribution.

To measure abstract task intensity at the geographic level, we take two additional steps. We first use the \(ATI\) index to identify the set of occupations that are in the top employment-weighted one-third abstract task intensity in 1980. We refer to these as abstract task-intensive occupations.

The choice of 67-percentile is consistent with the cut-off chosen Autor and Dorn (2013). In addition, as shown in Figure 13, abstract task intensity is strictly increasing in occupational skill.\(^{21}\)

\(^{20}\)Following Autor and Dorn (2013), we collapse ALM’s original five task measures to two task aggregates for abstract, and routine & manual tasks.

\(^{21}\)As a robustness check, we also perform the analysis by setting the cutoffs at 75-percentile and 50-percentile. The main results do not change.
Figure 13: Abstract Task-Intensive Occupations and Occupational Skill Rank

Source: Census IPUMS 5 percent samples for year 1980 and Census American Community Survey (1 percent) sample for 2010. All occupation in these samples refer to prior year’s employment. The figure plots share of abstract task-intensive employment by 1980 occupation skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations).

We next calculate for each MSA $c$ an abstract employment share measure, $ASH_{c,t}$, equal to:

$$ASH_{c,t} = \left( \sum_{k=1}^{K} N_{ckt} \cdot 1 \left[ ATI_k > ATI^{P67} \right] \right) \left( \sum_{k=1}^{K} N_{ckt} \right)^{-1}$$

where $N_{ckt}$ is the employment in occupation $k$ in MSA $c$ at time $t$, and $1[\cdot]$ is the indicator function, which takes the value of one if the occupation is abstract task-intensive by our definition.

Figure 2 plots the change in shares of abstract-intensive employment against metropolitan area population in 1980 and 2010. The left panel plots the data; the right panel plots a locally weighted regression for each year. From 1980 to 2010, larger cities experience a larger increase in the share of abstract task intensive employments.
A.3 Homogeneous Equilibrium: Definition and Stability

Traditional definition of stability is given by

\[ \frac{\partial V(z)}{\partial L} < 0 \quad \forall z \]

This approach is commonly used in the literature (see e.g. Behrens, Duranton and Robert-Nicoud (2014)). However, the analysis is straightforward if goods and labor markets clear city by city, i.e. individual utility function can be written as a function of the population in that location. In spatial equilibrium, if we shut down labor mobility, economic outcomes (in expectation) does not change. However, in our model, wage of production workers is determined by the spatial non-arbitrage condition, i.e. equation (3). If workers cannot move in equilibrium, clearing goods and labor market would require

\[ w_n = E(\pi_n(z_n^*)) \]

where \( \int_{z_n^*}^{\infty} a(z_n^*) l^\beta \mu(z, n) dz = (1 - \alpha)W_n. \)

Apparently, outcomes are very different from our spatial equilibrium case, where we pin down workers’ wage by the inseparability of labor market outcomes and labor mobility. To evaluate stability of equilibrium outcomes, we are adopting the approached developed by Davis and Dingel (2012). The idea is to maintain spatial equilibrium among production workers, and assess stability based on managers’ incentives to move.

We start from equilibrium allocation of \( \mu^*(z, n), \) and consider a perturbation in which a small mass of managers (and their corresponding production workers) move from one city (cities) to another (other cities). The equilibrium is stable if managers who moved would obtain higher utility in their equilibrium cities than in their new location.

**Definition 1:** A perturbation of size \( \epsilon \) is \( d\mu(z, c) \), a measure of skill \( z \) in city \( c \), satisfying:

1. \( L \cdot \sum_c \int_z |d\mu(z, c)| dz = 2\epsilon: \epsilon \) mass is moved.
2. \( \sum_c d\mu(z, c) = 0 \quad \forall z: \) Aggregate population is unchanged for all \( z. \)
3. \( \{c : d\mu(z, c) > 0\} \) is a singleton and \( \{c : d\mu(z, c) < 0\} \) is also a singleton: that is we move some agents from one single city to another city.
Definition 2: $\mu^*(z, c)$ is locally stable if there exists an $\bar{\epsilon} > 0$ such that:

$$\log v(z, c_1) \geq \log v(z, c_2)$$

such that $z > z^*$, $d\mu(z, c_1) < 0$ and $d\mu(z, c_2) > 0$ for all population allocations $\mu^*(z, c) = \mu^*(z, c) + d\mu^*(z, c)$ in which $d\mu$ is a perturbation of size $\epsilon \leq \bar{\epsilon}$; under $\mu^*(z, c)$, individuals maximize, markets clear and prices satisfy pricing equations.

Proposition 4 states that a systems of identical cities is not locally stable. We prove the results of this proposition below.

Proof: Without loss, suppose we move managers with City 1 to City 2.

Since $\log f(z, Z_c)$ is super-modular, the highest skilled producers have the most to gain from a move.

It is sufficient to consider a perturbation of size $\epsilon$ s.t. $[z^*(\epsilon), \infty]$ move from City 1 to City 2. The equilibrium is stable with respect to the perturbation if:

$$\frac{1}{(1-\beta)} \left[ \log f(\hat{z}, Z_{c2}') - \log f(\hat{z}, Z_{c1}') \right] \leq (1-\alpha)[\log p_2' - \log p_1']$$

where $\hat{z} = \sup\{z : \mu(z, 1) > 0\}$.

And we have:

$$\frac{1}{(1-\beta)} \left[ \log f(\hat{z}, Z_{c2}') - \log f(\hat{z}, Z_{c1}') \right] \leq$$

$$(1-\alpha) \log \left( wL_n w + \zeta \Phi^{\frac{1}{\alpha(1-\beta)}} \int_{z^*}^{\infty} f(Z_{c2}', z)^{\frac{1}{1-\beta}} \mu(z, n) dz \right) -$$

$$(1-\alpha) \log \left( wL_n w + \zeta \Phi^{\frac{1}{\alpha(1-\beta)}} \int_{z^*}^{\infty} f(Z_{c1}', z)^{\frac{1}{1-\beta}} \mu(z, n) dz \right)$$

This inequality is violated if $Z$ or $\hat{z}$ are sufficiently large, since $\log f(\hat{z}, Z_c')$ is unboundedly increasing in both $\hat{z}$ and $Z_c$.

A.4 Demand for Production Workers

We want to derive labor demand for production workers given by equation 11.
Denote \( X_{nc} = \frac{A_{nc}}{\tau_{nc} w_{c}^{\beta}} \), then from Proposition 1:

\[
G_{nc}(x) = Pr(X_{nc} \leq x) = Pr(A_{nc} \leq \tau_{nc} w_{c}^{\beta} x) = e^{-T_{nc}(\tau_{nc} w_{c}^{\beta})^{-\theta} x^{-\theta}}
\]

Joint distribution that a manager from city \( n \) locates her production team in city \( c \) and that \( \frac{A_{nc}}{\tau_{nc} w_{c}^{\beta}} = x \) is:

\[
Pr(\arg\max_{k} A_{nk} \tau_{nk} w_{k}^{\beta} = c \cap \frac{A_{nc}}{\tau_{nc} w_{c}^{\beta}} = x) = \theta T_{nc}(\tau_{nc} w_{c}^{\beta})^{-\theta} x^{-\theta-1} e^{-\Phi_{nc} x^{-\theta}}
\]

Given \( l_{nc}(z) = \beta^{\frac{1}{1-\beta}} w_{c}^{-1} f(Z_{n}, z) \left( \frac{\Phi_{nc}}{\tau_{nc} w_{c}^{\beta}} \right)^{\frac{1}{1-\beta}} \), we have:

\[
L_{w} = \beta L_{nc} w_{c}^{-1} \left[ \int_{z^*}^{\infty} (f(Z_{n}, z))^{\frac{1}{1-\beta}} \mu(z, n) dz \right] \left[ \int_{0}^{\infty} (\theta x^{-\theta-1} e^{-\Phi_{nc} x^{-\theta}}) x^{\frac{1}{1-\beta}} dx \right] = \eta L_{w}^{-1} (T_{nc}(\tau_{nc} w_{c}^{\beta})^{-\theta})^{\frac{1}{1-\beta}} \left[ \int_{z^*}^{\infty} (f(Z_{n}, z))^{\frac{1}{1-\beta}} \mu(z, n) dz \right]
\]

where \( \eta = \beta^{\frac{1}{1-\beta}} \int_{0}^{\infty} y^{-\frac{1}{\beta(1-\beta)}} e^{-y} dy \).

A.5 Two-City Model

For analysis below, we assume \( \tau_{12} = \tau_{21} = \tau \) and \( T_{12} = T_{21} = T \). \( Z_{n} \) are given by the following equations:

\[
Z_{1} = J(\int_{z^*}^{\tilde{z}} j(z) \cdot \mu(z) dz)
\]

\[
Z_{2} = J(\int_{\tilde{z}}^{\infty} j(z) \cdot \mu(z) dz)
\]

First consider distribution of managers in the two cities, which is determined by two skill cut-off points, \( z^* \) and \( \tilde{z} \). \( z^* \) and \( \tilde{z} \) are given by the occupation indifference condition and spatial indifference condition respectively.

\[
w_{1} = \zeta f(Z_{1}, z^*)^{\frac{1}{1-\beta}} \Phi_{1}^{\frac{1}{1-\beta}}
\]

\[
\frac{1}{\theta(1-\beta)} [\log \phi_{1} - \log \phi_{2}] + \frac{1}{1-\beta} [\log f(Z_{1}, \tilde{z}) - \log f(Z_{2}, \tilde{z})] = (1-\alpha) [\log p_{1} - \log p_{2}]
\]
where
\[ \Phi_1 = T(w_1^{-\beta \theta} + \tau^{-\theta} w_2^{-\beta \theta}), \quad \Phi_2 = T(w_2^{-\beta \theta} + \tau^{-\theta} w_1^{-\beta \theta}) \]

To determine, \( p_1, p_2, w_1, w_2 \), we have:

\[ \log w_1 - (1 - \alpha) \log p_1 = \log w_2 - (1 - \alpha) \log p_2 \]

\[ p_1 = (1 - \alpha)W_1 = (1 - \alpha) \left[ w_1 L_1^w + L \int_{z^*}^{\bar{z}} [f(Z_1, z)^{\theta \Phi_1} \frac{1}{\pi(1-\beta)} \mu(z) dz] \right] \]

\[ p_2 = (1 - \alpha)W_2 = (1 - \alpha) \left[ w_2 L_2^w + L \int_{\bar{z}}^{\infty} [f(Z_2, z)^{\theta \Phi_2} \frac{1}{\pi(1-\beta)} \mu(z) dz] \right] \]

\[ L_1^w + L_2^w = L \int_{0}^{z^*} \mu(z) dz \]

where \( L_1^w \) and \( L_2^w \) represent the number of production workers in City 1 and City 2, and are given by the two equations below:

\[ L_1^w = L_{11}^w + L_{12}^w \]

\[ = L \eta w_1^{-\beta \theta} \Phi_1^{1/(1-\beta)} \left( \int_{z^*}^{\bar{z}} f(Z_1, z)^{1/(1-\beta)} \mu(z) dz \right) + T \tau^{-\theta} w_1^{-\beta \theta} \Phi_2^{1/(1-\beta)} \left( \int_{\bar{z}}^{\infty} f(Z_2, z)^{1/(1-\beta)} \mu(z) dz \right) \]

\[ L_2^w = L_{22}^w + L_{21}^w \]

\[ = L \eta w_2^{-\beta \theta} \Phi_1^{1/(1-\beta)} \left( \int_{z^*}^{\bar{z}} f(Z_1, z)^{1/(1-\beta)} \mu(z) dz \right) + T \tau^{-\theta} w_2^{-\beta \theta} \Phi_2^{1/(1-\beta)} \left( \int_{\bar{z}}^{\infty} f(Z_2, z)^{1/(1-\beta)} \mu(z) dz \right) \]