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The geography of structural transformation: Effects on inequality and mobility

Kohei Takeda

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
The interplay between structural transformation in the aggregate and local economies is key to understanding spatial inequality and worker mobility. This paper develops a dynamic overlapping generations model of economic geography where historical exposure to different industries creates persistence in occupational structure, and non-homothetic preferences and differential productivity growth lead to different rates of structural transformation. Despite the heterogeneity across locations, sectors, and time, the model remains tractable and is calibrated with the U.S. economy from 1980 to 2010. The calibration allows us to back out measures of upward mobility and inequality, thereby providing theoretical underpinnings to the Gatsby Curve. The counterfactual analysis shows that structural transformation has substantial effects on mobility: if there were no productivity growth in the manufacturing sector, income mobility would be about 6 percent higher, and if amenities were equalized across locations, it would rise by around 10 percent. In these effects, we find that different degrees of historical exposure to industries in local economies play an important role.

Key words: structural transformation, upward mobility, labor mobility, economic geography
JEL codes: O14; J62; R11; R13

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1 Introduction

The last half-century has seen a remarkable structural transformation of the world. While there has been sustained deindustrialization and a general shift towards the service sector in most developed countries, there is a significant variation in the extent of this structural transformation across geography within a given country. While the causes and consequences of structural transformation have been well documented at a national level (see, for example Matsuyama 1992; Caselli and Coleman II 2001; Ngai and Pissarides 2007; Matsuyama 2009; Buera and Kaboski 2012; Herrendorf et al. 2014; Matsuyama 2019; Comin et al. 2021) , we know very little about what drives its variation across space within countries and how the structure of the spatial economy shapes individual outcomes. And, importantly, the uneven impact of this structural transformation could explain both spatial inequality and geographical variation in the social mobility of workers.

This paper (i) shows how amenities and productivity spillovers are the main drivers of the geographical unevenness of structural transformation and (ii) uses the model and fitted data to perform counterfactuals that allow us to trace out the consequences of this variation for inequality and mobility across cities in the U.S. To this end, we build a dynamic economic geography model that incorporates overlapping generations, multiple sectors and the frictional adjustment for workers who switch locations and industries. In their youth, workers' tastes for which industry to work in is a function the industries represented in their location of birth. Given their tastes for industry and locations, they choose cities and industries to work in later in their life, and this fuels the dynamics of labor allocation across industries. Incorporating overlapping generations of workers to characterize the evolution of labor allocation across space and industries is a novel extension of the economic geography model. Structural transformation in a given locality provides a tractable expression for understanding the key mechanisms that determine the spatial dynamics of total factor productivity (TFP), welfare, factor prices and intergenerational mobility. We then calibrate this model using data on the U.S. metropolitan areas (CBSAs) from 1980 to 2010 to obtain the amenity and productivity estimates that drive differential rates of structural transformation across locations and then trace out their effects on inequality and mobility.

In Section 2 we begin by describing the spatial variation of structural changes and its relation to upward mobility and industry choice of workers in the U.S. The findings suggest that the current labor composition of the local economy and the pattern of structural transformation can play a significant role in determining the upward income mobility of the next generation. Then, in Section 3 we propose the dynamic economic geography model, which has three key components: (i) structural transformation caused by both non-homothetic preferences and differential productivity growth across sectors, (ii) a multi-location and multi-sector version of the gravity model, and (iii) barriers for workers to switch locations and industries. Conditional on the technological progress in fundamental productivity, the non-homothetic preference of individuals between the manufacturing sector and services sector leads to a different slope of the Engel curve across workers in different locations and industries. We embed this mechanism of structural transformation in the multi-sector version of the gravity model and this enables us to consider the microstructure of spatial linkages in production and consumption. The different patterns of demand shifts by workers imply heterogeneous gains from trade by geography and sector, and disparity in real incomes leads to the localization and sector specialization of workers. These agglomerations are essential in the endogenous mechanisms creating the spatial variation of structural transformation and its relation to the spatial inequality in welfare.

Once we have defined the structure of demand, production and trade, we present an overlapping generation theory for workers' choice of local labor markets, which drives the dynamics of labor allocation. Individuals live for two periods. In the first period, individuals choose the location and industry that will be the focus of the second period. Individual workers' decisions on where to supply labor depend on two probabilities: (i) their location choice is determined by amenities, real income and mobility costs; (ii) the choice of an industry that reflects the future expected return and exposure to the previous generation's sectors of employment in their home local labor market. Conditional on the choice of industry, lower migration costs increase the opportunity for labor mobility on geography, allowing workers to move where higher returns from work exist, leading to welfare gains.

Turning to the industry choice of individuals in the first period, we introduce the simple microfoundation for the influence of the industrial composition in the previous generation on their choice. An individual receives information regarding jobs in an industry from the previous generation in the local labor market where they live in the first period. If there are a large number of workers in any particular industry among the previous generation, an individual in the next generation has more exposure to the industry and receives more information from it. This information leads to different taste values. An individual then decides on an industry that gives them the highest expected utility, taking into account their specific taste values. This, in turn, creates a path dependence in the local labor market over generations. Intuitively, an individual's choice of industry is affected by the degree of structural transformation in the local economy. This is consistent with a large body of sociological literature and empirical evidence from the study of the local labor market. In the model therefore, individuals' decisions feature two probability choices that take quite different roles in the transition of local labor markets. The former accounts for how local characteristics and spatial structure define labor supply, and the latter explains why the transition process of workers persists in some local economies.

In Section 4 we provide a quantitatively oriented theory to study the consequences of the distributional effects of structural change on workers' inequality over space and time. In equilibrium, the disparity of wages, consumption and sector-specific local agglomeration forces create cross-sectional inequality among workers. For upward mobility over generations, the two sets of workers' idiosyncratic preferences over locations and industries and the extent of structural transformation determine the equilibrium intergenerational income mobility. Therefore, our model speaks to the fundamental source of the variation of inequality and upward income mobility with a focus on the role of the geography of structural transformation.

After exploring the qualitative and quantitative insights in the theoretical model, in Section 5 we calibrate the model with the data from the 395 core based statistical areas (CBSAs) in the U.S.

and 17 industries in the manufacturing sector and the services sector, and a construction sector. We first estimate some parameters by exploiting the structural equations in the model. We use gravity equations for internal trade and migration to estimate their elasticities, and we then estimate key parameters that determine workers' industry choice based on the data on wage and employment by industry and CBSAs, leveraging the model structure. Subsequently, we invert the model to recover the time-varying fundamental productivity and amenities by industry and CBSAs for different periods, 1980, 1990, 2000 and 2010. While we allow for high dimensions in locations, industries and time, the model remains tractable and allows us to compute these fundamentals in the real economy. Based on the inverted fundamentals and computed workers' choice, we calculate the measured TFP, welfare and intergenerational inequality across space. The quantification highlights the quantitative importance of different margins in the model that determine the geographical variation of structural transformation and its impact on welfare and upward mobility, which are presented in Section 6.

Armed with the estimated parameters and inverted fundamentals in the U.S. economy, in Section 7 we first perform sets of counterfactual exercises varying (i) technological progress and (ii) local amenities. For the former, we conduct a counterfactual exercise where the evolution of fundamental productivity in the manufacturing sector shows different patterns to the baseline. Namely, we compute the counterfactual equilibrium when the fundamental productivity of manufacturing industries was fixed after a negative shock to the baseline economy in 1990. We find that such fundamental productivity growth drives spatial variation in structural change via differential productivity spillovers and demand shifts. Technological progress, on average, lowers the upward mobility of workers and we find pronounced geographical variation in this effect. For the latter, we carry out a counterfactual where we vary amenities across localities. In the model, fundamental amenities for workers are location and industry specific, and they include location-specific migration barriers and sector-specific taste shifters. In the counterfactual, we assume that the geographical variation of amenities becomes uniform so that every worker in any particular industry enjoys the same benefit from amenities across space. The result shows that the persistent variation of fundamental amenities is crucial for explaining the regional disparity in TFP changes and workers' mobility. This leads to the disparity in welfare and intergenerational income mobility among workers across CBSAs observed in the U.S. In addition to these counterfactuals for fundamental productivity and amenities, we also evaluate how non-homothetic preference and historical exposure effects in job choices are important for explaining the heterogeneity of structural transformation across locations and workers' intergenerational income mobility. We find that, even with time-varying fundamentals, the channel of demand-driven structural transformation through non-homothetic preference matters in explaining the variation of TFP growth and, therefore, the disparity in the mobility of workers. Lastly, we explore the importance of the exposure effects on the job choices of workers. Removing such exposure effects increases workers' mobility, which creates sorting of workers to productive places in *both* manufacturing and service sectors. As a result, workers end up attaining high intergenerational income mobility. This is suggestive of the importance of such persistence when taking into account the link between different degrees of structural transformation and the mobility of workers across space and time.

Our work is related to the line of discussions about the sources of different rates of growth in space, including input-output linkages (Puga and Venables 1996), innovation (Brezis and Krugman 1997; Duranton and Puga 2001), trade costs (Redding and Venables 2004; Duranton and Turner 2012; Allen and Arkolakis 2014), spatial spillover of technology (Desmet and Rossi-Hansberg 2009; Desmet and Rossi-Hansberg 2014). Among others, there are several papers on the role of structural transformation in differential growth between urban and rural, including Michaels et al. (2012), Eckert and Peters (2022) and Fan et al. (2021). We make two contributions to this line of work. First, integrating those different sources of spatial heterogeneity in a tractable way, we present the parsimonious model calibrated to quantitatively evaluate their roles in the differential rate of structural transformation. Second, we provide the microfoundation that creates persistence in the local labor market over time and trace out its consequences for inequality and intergenerational mobility across locations.

Our theory adopts the recent modeling of non-homothetic preferences in structural transformation of macroeconomics, including Matsuyama (2019) and Comin et al. (2021). We first incorporate the non-homothetic constant elasticity of substitution demand system to evaluate the role of heterogeneous Engel curves across workers in the pattern of structural transformation and welfare disparity within a country. The modeling approach of dynamics is closely related to that of Allen and Donaldson (2022) and Pellegrina and Sotelo (2021). Our contribution is twofold. First, we emphasize the cross-generational spillovers in a taste of workers in their occupational choice in lieu of productivity shocks based on our motivating evidence. Consequently, our model derives a new implication of the spatial pattern in structural transformation in formalization of the intergenerational income mobility. Second, we propose the methodology to back out the measures of productivity, amenities, inequality and upward mobility from fundamental information on local labor markets without relying on specific shocks. This allows us to perform various counterfactual experiments to study external shocks and their consequences of inequality among workers from both cross-sectional and intergenerational perspectives.

Lastly, as an essential contribution, this paper is related to the discussion on intergenerational mobility, including Ferrie (2005), Long and Ferrie (2013), Chetty et al. (2014), Feigenbaum (2015), Bütikofer et al. (2019), Fogli and Guerrieri (2019) and Boar and Lashkari (2021). This paper contributes by providing a structural approach to understanding how the industrialization of an economy can influence patterns of inequality and mobility in different locations. In particular, we connect the two phenomena which have shaped the economy in the last half-century – structural transformation from manufacturing to services and fall in social mobility – in a quantifiable general equilibrium model. This approach and our quantitative results complement the evidences and provide microfoundations for the Great Gatsby Curve that the late Alan Krueger originally pointed to.

In summary, the power of the framework developed in this paper is that it is tractable and is capable of performing various counterfactual exercises to study policy interventions and their consequences of inequality among workers from both cross-sectional and intergenerational perspectives. The key finding is that the interplay between structural transformation in the aggregate and local economies is critical for understanding spatial inequality and worker mobility. The dynamic nature of our spatial model allows us to study phenomena that have received limited scrutiny but which are of fundamental interest in a country that is increasingly riven by growing inequality and barriers to upward mobility. We begin to understand why citizens in different cities in the same country have such different outcomes. Why some remain mired in the Rust Belt with limited prospects whilst others reside in the most dynamic cities on earth. We also begin to glimpse why rising inequality might constrain upward mobility thus providing microfoundations for the Great Gatsby Curve that the late Alan Krueger originally pointed to. These issues of inequality and limited mobility are perhaps the most important facing not just the U.S. but a whole range of countries across the world. This paper contributes by opening the black box of how the structure of economy can influence patterns of inequality and mobility in different locations.

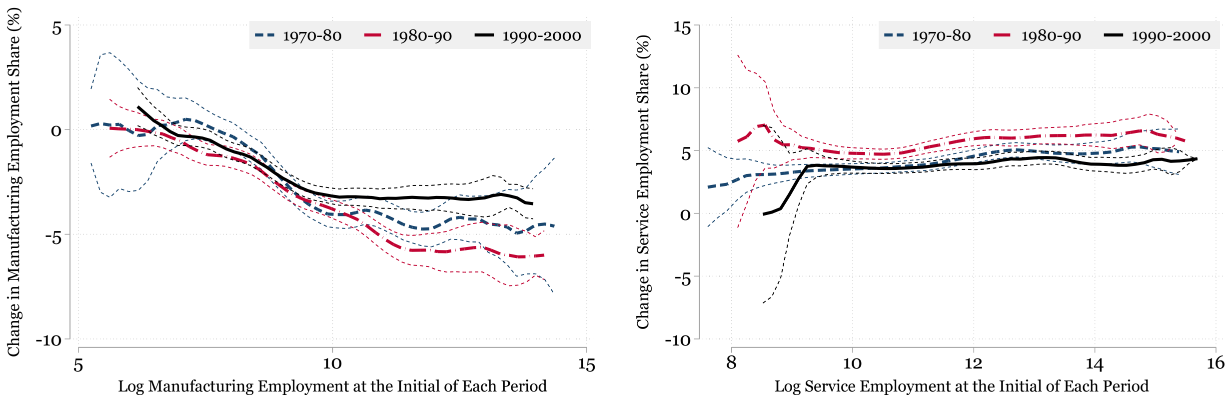
2 Motivating Evidence

In this section we start by documenting the variation of structural transformation across different places in the U.S. Then, we relate it to the spatial variation of intergenerational income mobility of workers. To understand the potential mechanisms behind the relationship, we then examine how exposure to structural transformation within localities affects workers' occupational structure.

Spatial Variation of Structural Transformation. Figure 1 illustrates the relationship between changes in employment share and initial employment level across CBSAs for the manufacturing sector and services sector over different periods, using the data on sector level employment from the U.S. Bureau of Economic Analysis (BEA). We display the three different periods: 1970-1980; 1980-1990; and 1990-2000. In the left-hand panel, we find that cities with large initial employment in the manufacturing sector experienced a significant shift of workers away from the manufacturing sector during each period. This pattern indicates that cities with a large manufacturing sector have led the deindustrialization of the U.S. economy, despite the fact that it became less pronounced between 1990 and 2000. In the right-hand panel, we find a relatively flat relationship between the change in the employment share of the services sector and the initial size of employment in the sector. This suggests that, in contrast to the manufacturing sector, the spatial variation in the employment share of services has not changed dramatically over the past few decades.

Another observation in these figures is that there is a relatively large variation in the change of employment composition for cities with a large manufacturing sector employment and a relatively small services sector employment. In these figures, the confidence intervals for these cities become expansive. One logic that creates the spatial variation in this structural transformation among these locations is the differential productivity growth balancing fundamental technological differences and productivity spillovers. If agglomeration forces are sufficiently strong relative to fundamental technological progress, locations lag behind in terms of the shift of employment from the manufacturing sector. Consequently, our theoretical framework allows both spatial het-

Figure 1: Spatial Variation of Structural Transformation in the U.S.



(a) Manufacturing

(b) Services

Note: These figures show the polynomial fitted line (local mean smoothing) for the change in employment share between different periods: 1970-1980, 1980-1990 and 1990-2000. Figure (a) shows that for the manufacturing sector, and Figure (b) shows that for the service sector. The sample includes core based statistical areas (CBSAs) in the U.S. where change in employment shares are well defined in the BEA data for each time period. The dotted lines show 95% confidence intervals.

erogeneity in fundamental productivity growth and spillovers.

Another potential driver of this geographical unevenness in structural transformation is a disparity in demand. In the U.S., there is considerable variation in expenditure share across cities.[1] To reconcile this, we incorporate the non-homothetic preferences of individuals in the model, which results in the different slopes of the Engel curve for workers by their location and industry.

Given the variation of the structural transformation within the country, an interesting question is how they are related across locations. For instance, the citizens of San Jose or Tuscon may be on entirely different trajectories of structural transformation if they are proxy to cities like Detroit and Cleveland. Theoretically, three endogenous mechanisms can create the spatial relations in structural transformation. First, the spatial extent of spillovers in productivity is not necessarily local but can also be diffused across locations, which can lead to a similar pattern of structural transformation within such spatial extent. The second mechanism is the frictional labor adjustment across locations and workers' factor specificity. Suppose that a particular location sees a positive productivity shock in the manufacturing sector, which leads to more employment in the services sector and complementarity between sectors leads to an expansion of expenditure share in services. Together, workers in the manufacturing sector move to other locations incurring migration costs, which lowers the wages in the manufacturing sector in other locations close to the origin. This shifts workers away from the manufacturing sector in such locations. Third, trade costs between locations matter to explain how demand for services in any particular location induces structural change in other locations that export services to the location.

To see the spatial relationship in structural transformation, we consider the following regres-

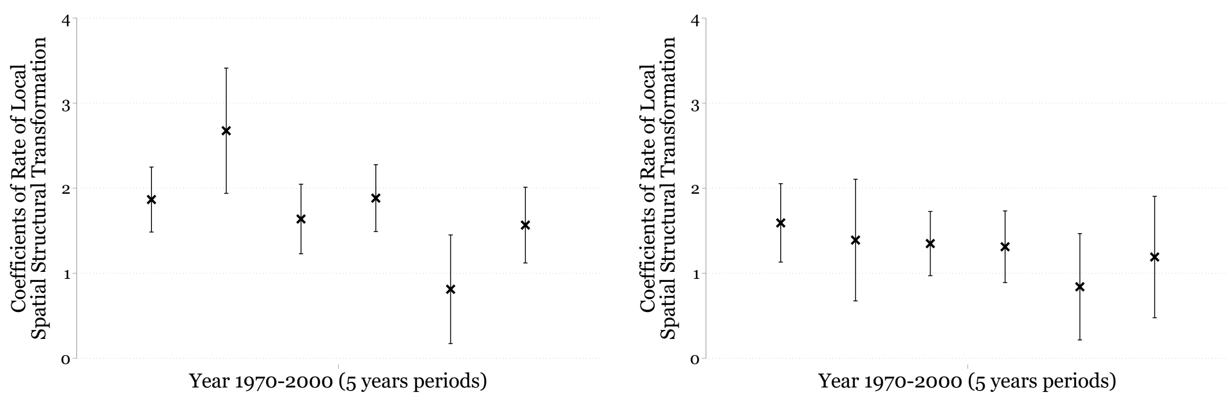
[1]See the supplementary material for the expenditure share for a selection of representative U.S. cities.

sion for any particular period t:

$$\Delta \text{EmpShare}^{j}_{it} = \alpha_t + \beta^{j}_{0t} \ln \text{Emp}^{j}_{it-1} + \beta^{j}_{1t} \sum_{n \in \mathcal{C}_i} \frac{\Delta \text{EmpShare}^{j}_{nt}}{\text{dist}_{in}} + u^{j}_{it}, \tag{1}$$

where i and n index locations (e.g., CBSAs) and j corresponds to sector, $\ln \text{Emp}^{j}_{it-1}$ is size of employment in i for sector j at the period $t-1$, $\Delta \text{EmpShare}^{j}_{it}$ is change in employment share in i for sector j between the period $t-1$ to t, dist_{in} is a geographical distances between i and n, and u^{j}_{it} is a stochastic error. $\mathcal{C}_i$ denotes the set of locations around i excluding own. Hence, the measure of $\sum_{n \in \mathcal{C}_i} \frac{\Delta \text{EmpShare}^{j}_{nt}}{\text{dist}_{in}}$ captures the rate of structural transformation in localities around i with the decay of distances and coefficients of our interest are β^{j}_{1t}. We use the BEA data of employment share and employment size at CBSA level and great circle distances between CBSAs. We define $\mathcal{C}_i$ as the set of CBSAs that locate within 1,500 km from CBSA i. For the time periods, we see every five years period from 1970 to 2000. Figure 2 displays results.

Figure 2: Geography of Structural Transformation in the U.S.



(a) Manufacturing

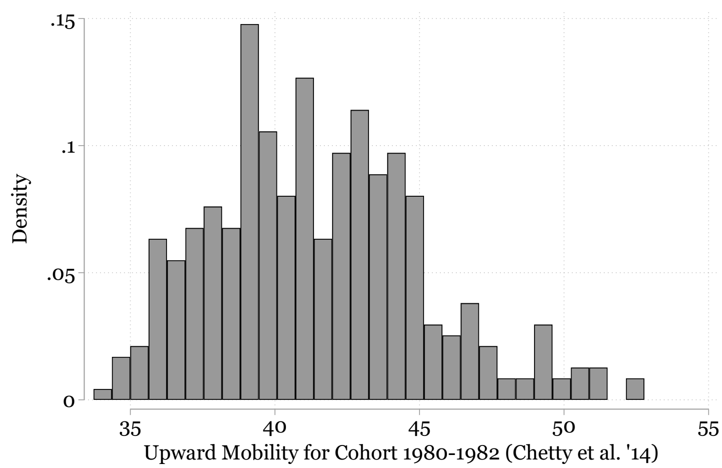
(b) Services

Note: These figures show estimated coefficients of the cross-sectional regression (1). Each coefficient corresponds to different periods, respectively: 1970-1975, 1975-1980, 1980-1985, 1985-1990, 1990-1995 and 1995-2000 (from the left to the right). Figure (a) shows results for the manufacturing sector, and Figure (b) shows those for the services sector. The sample includes core based statistical areas (CBSAs) in the U.S. where changes in employment shares are well defined in the BEA data for each time period. The lines show 95% confidence intervals.

For both the manufacturing and services sectors, we find positive and statistically significant estimated coefficients. This implies that the rate of change in employment composition in any given city is positively associated with the rate of structural transformation in their localities conditional on the initial employment size. This is suggestive of the spatial regularity of structural transformation. Comparing these two sectors, the coefficients for the manufacturing sector are larger than those for the services sector. We interpret this result as supporting the idea that the different rates of structural transformation across geography have been related to the uneven distribution of industries in a country. In our theoretical framework, the forementioned three endogenous mechanisms, together with heterogeneity in fundamental productivity and amenities, create the spatial pattern of structural transformation.

Intergenerational Mobility. The declining intergenerational income mobility has attracted enormous interest in the U.S. Following Chetty et al. (2014), the measure of the upward mobility of workers in terms of their income represents the expected rank for children from families with below-median parents' income in the national distribution. We utilize the values from Chetty et al. (2014) and focus on their variation in the United States and their relationship to structural transformation. Figure 3 shows a variation of the intergenerational mobility of workers across cities. Among 373 MSAs, the average level of the measures is 41.45 and those at the 90th percentile of the distribution are 46.18, while those at the 10th percentile are 36.88. Even among large cities, the measure of intergenerational income mobility varies widely: New York (43.92), San Francisco (44.50) and Pittsburgh (44.79) indicate a high degree of upward mobility, while Chicago (39.53), Atlanta (36.14) and Detroit (37.30) indicate a low degree of upward mobility. This spatial variation across cities in the upward mobility of workers is our focus.

Figure 3: Intergenerational Income Mobility across the U.S. Cities

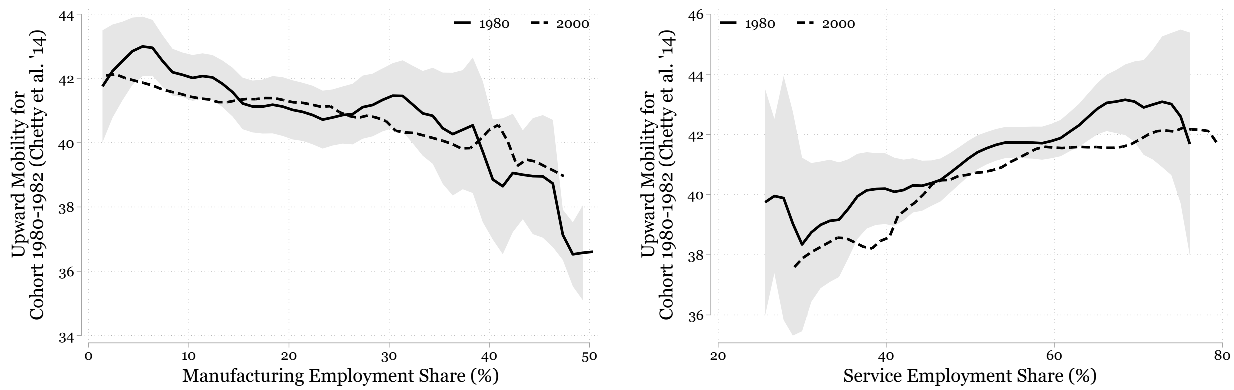


Note: The measure of the absolute upward mobility comes from Chetty et al. (2014): the expected income rank for children from families with below-median parents' income in the national distribution. Each observation represents metropolitan areas (MSAs).

We next examine the relationship between the upward mobility of workers and structural transformation in the U.S. cities. Figure 4 provides a visualization of the gradient between the rates of intergenerational mobility and employment shares in different sectors for the U.S. cities. In the left-hand panel, we observe the negative relationship for the manufacturing sector. This implies, based on the employment share in 1980, that workers born in manufacturing cities are less likely to achieve higher positions in the income distribution in the future. Although this negative relationship is less pronounced evaluating the employment share in 2000, workers from cities where sustained manufacturing employment expect to have upward mobility. In contrast, the right-hand panel shows the positive relationship between upward mobility and employment share in the services sector. Workers with origins in the cities where more workers were in the services sector or employment shifted to the services sector are more likely to climb up the income ladder compared to previous generations.

Taken together, these observations suggest that the different rates of structural transformation

Figure 4: Geography of Structural Transformation and Intergenerational Mobility across the U.S. cities



(a) **(b)**

Note: These figures show local polynomial regressions for metropolitan areas (MSAs). The vertical axis is the measure of the absolute upward mobility from Chetty et al. (2014). The measure is the expected income rank for children from families with below-median parents' income in the national distribution. The horizontal axis is the percentage of employment in the manufacturing sector (Panel (a)) and services sector (Panel (b)) for 1980 or 2000. The gray shading areas show 95 percent confidence intervals for 1980. The data on employment share is from BEA.

across locations within a country are related to the spatial variation of intergenerational income mobility. In particular, we notice that locations with sustained employment in the manufacturing sector show relatively lower upward mobility. In our theoretical model and its quantification, we seek to understand the potential mechanisms for the relationship.

Location of Origin for Workers. We next examine why different rates of structural transformation in workers' origins are relevant to their upward mobility. The potential mechanism of our interest is the persistence in the choice of work over generations. Intuitively, an individual worker with more exposure to manual manufacturing workers in Cleveland (origin place) continues to look for manufacturing jobs, thereby missing out opportunities in the services sector which makes up an increasing share of the U.S. economy. This means that the different patterns of structural transformation across locations have effects on both inequality across localities but also on the upward mobility of workers within localities. To see this effect of local exposure to industries, using samples from the 2011–2015 American Community Survey (ACS), we estimate a regression of the share of workers working in industry j who were born in state n (origin) on the share of employment in that industry j in state n during 1976-1980. We use 18 industries defined based on 4 digit SIC 87 that we also use in the calibration later and 49 states in the U.S.[2] Results are shown in Table 1.

In columns 1 and 2 of Table 1, we find that the proportion of the cohort working in the particular industry is large when the employment share of the industry was large in their origin place. As employment share in a particular industry in the origin doubles, the proportion of the cohort from the state working in that particular industry increases by around 24 percent and this positive rela-

[2]We exclude Alaska and Hawaii and include the District of Columbia.

Table 1: Workers' Industry Choice and Exposure to Industries in their Origin

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of Cohort 1976-80 in Industry, 2011-15					
Average Employment Share of Industry in the Origin of Workers over the years 1976-80	0.2443[a]	0.0010[a]	0.1791[a]	0.0010[a]	0.3560[a]	0.0014[a]
	(0.0293)	(0.0002)	(0.0264)	(0.0002)	(0.0571)	(0.0005)
State indicator	✓	✓	✓	✓	✓	✓
Industry indicator	✓	✓	✓	✓	✓	✓
Workers in different state of origin		✓		✓		✓
Workers in manufacture sector			✓	✓		
Workers in service sector					✓	✓
N	879	876	487	484	392	392
R^2	0.980	0.978	0.925	0.882	0.972	0.967

Note: Share of cohort 1976-80 in the industry during the period 2011-15 is the proportion of workers in any particular industry among those who were born in 1976-80 and have the same origin state. The average employment share of an industry in origin is defined by taking the average employment share of the industry in any particular state over five years, 1976-80. All regressions include indicator variables of state for 49 states and industry for 18 industries. In columns 1 and 2, we use all industries. In columns 3 and 4, we focus on workers in the manufacturing sector and construction sector, while in columns 5 and 6, we focus on those in the service sector. The classification of industries is in the Appendix. In columns 2, 4 and 6, we restrict the sample to workers who work in different states from their origin in 2011-15. Heteroskedasticity robust standard errors are in parentheses. *a*: Significant at the 1% level.

tionship holds for workers who work in states other than their state of origin. In columns 3 and 4 of Table 1, we present the analogous results for workers in manufacturing industries in 2011-2015. In columns 5 and 6 of Table 1, the positive effects are pronounced when we focus on workers in the service sector. This suggests that the industry choice of workers in the future period is related to the composition of employment across industries in their origin. In our theoretical model we introduce the microfoundation of workers' learning about the potential industries in their origins and characterize the persistence in their industry choices.

We now seek clarity on the source of the persistence in workers' industry choices. In particular, we provide evidence that the industry composition in the place of origin has small effects on the earnings of workers. To see this, we decompose the average earnings of workers into their origin state, current state and industry of work. In particular, we regress the logarithm of average labor earnings of workers in ACS 2011-15 on the logarithm of the total count of workers in the industry and current state, average employment share of the industry in their origin state, indicators of industry, indicators of current state and indicators of origin state. Our focus in this regression is the coefficients of the average employment share in 1976-80 of the industry that they work in 2011-15. Table 2 reports the results. In Column 1, we find that the effect of the employment share in the state of origin on labor earnings is not statistically different from zero. In column 2, we focus on workers in a different state to their origin and in columns 3 and 4, we only examine workers in different sectors: the manufacturing sector and construction sector (column 3) and the service sector (column 4). If exposure to industry directly affects the productivity of workers, the variation of average labor earnings of workers could reflect the effect. However, as can be seen, there is a limited effect of industry exposure in origin on their future labor earnings from the industry conditional on the current labor market. Therefore, we introduce persistence in the local labor market over generations through workers' preferences in job choices rather than the direct effect through labor productivity in our theoretical model.

Table 2: Workers' Earnings and Exposure to Industries in their Origin

	(1)	(2)	(3)	(4)
	Log of Average Labor Earnings of Workers, 2011-15			
Average Employment Share of the Industry in the Origin of Workers over the years 1976-80	0.1597 (0.2640)	0.1939 (0.2758)	0.1703 (0.4736)	0.1608 (0.3537)
Log total number of workers in current state and industry	✓	✓	✓	✓
State indicator (origin and current state)	✓	✓	✓	✓
Industry indicator	✓	✓	✓	✓
Workers in different state of origin		✓		
Workers in manufacture sector			✓	
Workers in service sector				✓
N	21,242	20,372	8,310	12,932
R^2	0.178	0.178	0.147	0.210

Note: Average employment share of industry in origin is defined for each industry by taking the average employment share of the industry in any particular state over five years, 1976-80. All regressions include indicator variables of origin and current state (49 states) and industry (18 industries). In column 1, we use all workers. In column 2, we restrict the sample for workers who work in a different state in 2011-15 from their origin. In column 3, we focus on workers in the manufacturing sector and construction sector, while in column 4, we focus on those in the service sector. Heteroskedasticity robust standard errors are in parentheses.

The spatial heterogeneity of structural transformation gives rise to the question of its redistributive effects across locations and over generations. In particular, this section's findings suggest that the current labor composition of the local economy and the pattern of structural transformation can play a significant role in determining the upward income mobility of the next generation. Then, the following questions draw our attention. What are the underlying drivers that create the spatial variation of structural transformation? How do the different rates of structural transformation have persistent effects on occupational structure? What is their quantitative importance in explaining the spatial inequality and upward mobility of workers in the U.S. economy? To address them, in the next section, we develop a quantifiable model to consider the variation of upward mobility and its relation to structural transformation.

3 A Model of the Geography of Structural Transformation

This section presents a model to understand the spatial heterogeneity of structural transformation and its consequence on workers over generations. The basic environment is the following. Time is discrete. A single country $\mathcal{N}$ consists of a discrete number of locations. We let $\mathcal{K}$ denote the set of $K+1$ industries. Among them, there are K tradable industries and a single sector providing the structure or housing services, which we refer sector 0. Locations are different in fundamental productivity and amenities. Immobile landlords own the land and the total units of land are unchanged over time. At generic time t, the economy is inhabited by two overlapping generations of equal size $\bar{L}$: the old born at period $t-1$ and the young born at period t. Only the old work and consume with each of them supplying a unit of labor inelastically. Accordingly, at any time, $\bar{L}$ also represents the total number of consumers and workers in the economy. Young workers decide in which location to live and in which industry to work when old, thus potentially giving rise to intergenerational changes in employment across local labor markets. In this respect, the first period of individuals is the *formative years*.

3.1 Demand, Mobility and Exposure in Local Labor Market

We consider the individuals' decisions regarding consumption, industry to work and location. At the initial of time $t-1$, people of generation t are homogeneous ex ante.[3] During the period $t-1$, individuals in location i observe the idiosyncratic taste shocks relating to the industry choice. They anticipate the wage and prices in the next period t and compute the expected payoff for the future. Given the expected payoff, they decide the industry, and we take that choice to be unchanged later. At the initial of period t, individuals draw and observe the taste shocks across locations and they decide location n where they live in period t. They move to the destination at the initial of period t subject to bilateral migration costs. In the location, they supply one unit of labor inelastically and decide consumption allocations. The lifetime utility of a worker ω of generation t who lived in i in period $t-1$ and works and consumes in location n and industry j in period t is:

$$\ln U^j_{nit}(\omega) = \ln B^j_{nt} + \ln C^j_{nt}(\omega) - \ln D_{nit} + \ln z^j_{it}(\omega) + \ln v_{nt}(\omega),$$

where $C^j_{nt}(\omega)$ is subutility function associated with consumption of individuals; B^j_{nt} is utility benefit from amenities common to sector j workers living in n; D_{nit} is migration cost from location i to n that reflects any impediments for movers. The idiosyncratic taste shocks from industry choice $z^j_{it}(\omega)$ depend on the origin of the worker. The second idiosyncratic shock of amenities related to location choices $v_{nt}(\omega)$ depends on the destination but is independent across i and j.

For the demand system, our objective is to study the implication of demand heterogeneity across workers and locations along with the structural transformation in the economy. Therefore, we depart from the standard CES aggregation by introducing a heterogeneous income effect across sectors, keeping tractability in the substitution effect as in Matsuyama (2019) and Comin et al. (2021). Workers of generation t working in location n and sector j receive income W^j_{nt} which includes labor earnings (wage) and surplus distributed among workers. We refer $\{p^k_{nt}\}$ to price of consumption of goods. The expenditure share of a worker with income W^j_{nt} is:

$$\psi^j_{k|nt} = \alpha_k^{\sigma-1}\left(p^k_{nt}/P^j_{nt}\right)^{1-\sigma}\left(W^j_{nt}/P^j_{nt}\right)^{\mu_k-1}, \quad \text{for all } k \in \mathcal{K} \tag{2}$$

where $(\{\alpha_k\}, \sigma, \{\mu_k\})$ are exogenous preference parameters[4] and $\{P^j_{nt}\}$ is the aggregate price index corresponding to the optimal consumption patterns for workers in sector j and location n that solves:

$$P^j_{nt} = \left(\sum_{k\in\mathcal{K}} \alpha_k^{\sigma-1}(p^k_{nt})^{1-\sigma}(W^j_{nt}/P^j_{nt})^{\mu_k-1}\right)^{1/(1-\sigma)}. \tag{3}$$

We emphasize the three key elasticities for this demand system (2). First, the elasticity of substitution between sectors is constant, $1-\sigma$. Second, the elasticity of *relative* demand between two different sectors to the *aggregate demand* is specific to the pair of sectors and governed by μ_k by sector. Third, income elasticity varies across sectors and depends on expenditure patterns: individuals exhibit higher income elasticity of demand for the industry with a large μ_k. When expenditure

[3] This can be easily extended to allow exogenous heterogeneity including race and gender.

[4] We assume $(\mu_k-\sigma)/(1-\sigma) > 0$ for all industries to ensure the global monotonicity and quasi-concavity of the consumption aggregation.

shifts to an industry with a large μ_k, the income elasticity of consumption becomes lower as the relative slopes of Engel decline for all sectors.[5]

Labor Mobility. Turning to the location choice of workers, we formally posit the following for the stochastic factor:

Assumption 1 *An individual draws vector $\{v_{it}(\omega)\}_{i\in\mathcal{N}}$ from the time invariant multivariate distribution: $G(\{v_{it}(\omega)\}) = \exp\left(-\sum_i (v_{it})^{-\varepsilon}\right)$. $v_{it}(\omega)$ and $v_{nt}(\omega)$ are independent for any $i \neq n$.*

The shape parameter reflects the dispersion of the idiosyncratic utility. Under Assumption 1, the probability that a worker born in i at period $t-1$ ends up working in location n at period t conditional on choosing industry j equals:

$$\lambda^j_{nit} = \left(\frac{B^j_{nt}\mathcal{W}^j_{nt}}{D_{nit}\bar{U}^j_{it}}\right)^{\varepsilon} \quad \text{with} \quad \bar{U}^j_{it} = \left(\sum_{\ell\in\mathcal{N}}\left(B^j_{\ell t}\mathcal{W}^j_{\ell t}/D_{\ell it}\right)^{\varepsilon}\right)^{1/\varepsilon}, \tag{4}$$

where $\bar{U}^j_{it}$ is expected utility conditional on job choice j. By the law of large numbers across a continuum of individuals, each element of the matrix $\{\lambda^j_{nit}\}$ is the share of movers among individuals of generation t conditional on industry choice j. The share becomes large when the destination exhibits higher real income from consumption ($\mathcal{W}^j_{nt} \equiv W^j_{nt}/P^j_{nt}$) associated with the adjustment of amenity value (B^j_{nt}) and discount of migration costs (D_{nit}). Therefore, $\bar{U}^j_{it}$ reflects the land of job opportunities for individuals born in i when working in industry j.

Learning and Choice of Industries. We turn to the distribution of idiosyncratic taste shocks relating to the choice of industry, $\{z^j_{it}(\omega)\}$. Consider an individual of generation $t+1$ with origin i. A such individual receives a discrete number of taste shocks for each sector from the previous generation t during the formative period, t and an individual spends an entire time on job choice during the period.

An individual acquires information containing taste shock from existing workers in the local labor market. An individual split one unit of time into T time spans with intervals Δ. Let g^j_{it} refer to the probability that she receives the valuable information during Δ. Within each time span, an individual decides time allocation across different industries to maximize the logit of probabilities of receiving valuable shocks. We let $\mathcal{O}(g^j_{it}, L^j_{it})$ denote the time required to achieve the probability g^j_{it}. This is increasing in g^j_{it} and decreasing in L^j_{it}. Intuitively, the marginal time needed for obtaining valuable information becomes small if there is a large pool of existing workers. For the objective function, an individual maximizes the average of odds that captures the chance of receiving valuable taste shocks relative to valueless ones regarding industries. Specifically, during

[5] Alternative non-homothetic preferences include: Stone-Geary preference; price independent generalized linearity (PIGL) preference (Buera and Kaboski 2012; Eckert and Peters 2022); constant ratio of income elasticity (Fieler 2011; Caron et al. 2014); income specific elasticity of substitution between goods (Handbury 2021). Compared to them, features of the non-homothetic CES demand system gain tractability and entail the core mechanisms of demand shift.

time span Δ, an individual of generation $t+1$ in location i solves the following problem:

$$\max_{\{g^j\}\in(0,1)} \sum_{j\in\mathcal{K}} \ln \frac{g^j}{1-g^j} \text{ s.t. } \left\{ \sum_{j\in\mathcal{K}} \mathcal{O}(g^j, L^j_{it}) \leq \Delta, \text{ and } \mathcal{O}(g^j, L^j_{it}) \equiv \frac{1}{\zeta_{jt}} \ln\left(\frac{1}{1-g^j}\right)(L^j_{it})^{-\eta} \right\}, \quad (5)$$

and we let g^j_{it} refer to its solution. The first constraint is time constraint. In the specification for $\mathcal{O}(g^j_{it}, L^j_{it})$, ζ_{jt} and η are strictly positive parameters: ζ_{jt} is a scale shifter and η quantifies how much an individual can save time when there are more existing workers in the local labor market.

Taking the limit $\Delta \to 0$, the problem above can lead to the number of shocks an individual of generation $t+1$ receives during a unit of time following Poisson distribution with arrival rate g^j_{it}. Further, to gain the tractability, the value of each shock is supposed to be following Pareto distribution with the shape parameter ϕ and shocks are independent. A small value of ϕ implies fat tail distribution for the size of shocks. Intuitively, if ϕ becomes small, an individual is more likely to receive a higher value of shock in job choice, leading to more idiosyncrasy in the industry choice. Summarizing the assumptions about the taste shocks that an individual of cohort $t+1$ receives:

Assumption 2 *An individual of cohort $t+1$ solves (5) and we consider the limit case $\Delta \to 0$ to characterize the distribution for the number of arrival shocks. The value of each taste shock follows independent Pareto distribution with shape parameter $\phi > 1$.*

This assumption argues that individuals face the *consideration set* when deciding future industry and location of work, and the set is influenced by workers' exposure to the historical employment composition. Given the set, individuals make their decisions following subjective expectations about future returns. Let $\{m^j_{it}(\omega)\}$ be the number of shocks an individual receives. An individual decides industry j to work in if and only if:

$$j \in \left\{ k \;:\; \max_{m\in\{1,2,\cdots,m^k_{it}(\omega)\}} \bar{U}^k_{it} z^{k\,(m)}_{it} \geq \max_{s\in\mathcal{K}} \max_{m\in\{1,2,\cdots,m^s_{it}\}} \bar{U}^s_{it} z^{s\,(m)}_{it} \right\}.$$

Under Assumption 2, the share of cohorts $t+1$ in location i that choose industry j becomes:

$$\kappa^j_{it+1} = \zeta_{jt}(L^j_{it})^{\eta} \left(\frac{\bar{U}^j_{it+1}}{V_{it+1}}\right)^{\phi} \quad \text{with} \quad V_{it+1} \equiv \left(\sum_{k\in\mathcal{K}} \zeta_{kt} \left(L^k_{it}\right)^{\eta} \left(\bar{U}^k_{it+1}\right)^{\phi}\right)^{1/\phi}. \quad (6)$$

The matrix $\{\kappa^j_{it}\}$ closes the individuals' decision process.[6]

The share of individuals depends on three components. The shifter ζ_{jt} translates the macro effect in the industry choice that is common across locations. The large probability of choosing sector j is associated with the large size of employment in the previous generation (L^j_{it}): more existing workers in the local labor market can save the marginal cost of information acquisition and it turns to be a large expected number of shocks that arrive to young generation *ceteris paribus*. Intuitively, the more people you meet who work there, the more likely you meet someone who

[6] Appendix A presents the details of derivation.

prefers it and transmits to you the love for the profession. This result can be interpreted as a path dependence in job choices in the local labor market over generations. Lastly, individuals of cohort $t+1$ choose sector j with high probability when conditional expected utility ($\bar{U}^j_{it}$) is large since it determines the advantage of industry j in terms of net gain for their future.

This formulation under Assumption 2 is related to empirical evidence of intergenerational linkage in job choices and work behavior.[7] As a particular mechanism, the specification may capture the path dependence in the local labor market through education. For some U.S. manufacturing cities, including Buffalo, Cincinnati and Youngstown (Ohio), the industrial specialization leads to underinvestment into education: workers of steelmaking or paper-pulping tied to specialized industries did not have any motivations for higher education or education for the new technology in services.[8] The specification of workers' idiosyncratic taste shocks also reflects the recent literature on the intergenerational transmission of preference apart from the endogenous creation of human capital or productivity.[9]

3.2 Technology and Trade

The production side builds on the multi-sector and multi-location Ricardian model embedded with input-output linkages and externalities from agglomeration. In each sector, there are final good producers and intermediate good producers. In each location, final good producers supply consumption goods and materials in a competitive fashion that are consumed locally. They use sector-specific intermediate goods, and their technology is constant elasticity of substitution.[10]

Intermediate goods' as well as the factors' markets are perfectly competitive. Intermediate goods are produced using labor and materials exploiting a Cobb-Douglas function. Firms face location and sector specific productivity $\{Z^j_{it}\}$ and firm specific productivity that is drawn from Fréchet distribution with shape parameter $\theta_j > 1$ in the wake of Eaton and Kortum (2002). Intermediate goods can be traded incurring a iceberg trade cost, so that delivering one unit of an intermediate good from n to i requires $\tau_{int} \geq 1$ units, with $\tau_{iit} = 1$. The probability that final producers of sector j in location i source intermediate goods from location n is:

$$\pi^j_{int} = \frac{\left(\tau_{int}\Xi^j_{nt}/Z^j_{nt}\right)^{-\theta_j}}{\sum_{\ell\in\mathcal{N}}\left(\tau_{i\ell t}\Xi^j_{\ell t}/Z^j_{\ell t}\right)^{-\theta_j}} \quad \text{with} \quad \Xi^j_{nt} = \left(w^j_{nt}\right)^{\beta_j}\prod_{k\in\mathcal{K}\backslash 0}(p^k_{nt})^{\beta_{jk}} \tag{7}$$

[7]The intergenerational linkage in the job choice found in the literature is one potential feature behind the recent trend of intergenerational mobility, as discussed in Corak (2013). Loury (2006) showed that around half of jobs are found in the network among relatives and friends in the U.S., and the highest wage was paid to workers who found the job through male relatives in the prior generation, and Kramarz and Skans (2014) showed that young workers find the first stable job in a parent's firm, and the effect is more substantial for low skilled jobs. Corak and Piraino (2011) found direct evidence on intergenerational transmission of employers in Canada.

[8]To consider the movement of people for education, we extend the baseline model to include the additional choice of individuals for education. See Subsection 3.5 for further discussion.

[9]The relationship between generations in job choice can be explained by the (unobserved) transmission of taste or preference through formal or informal social interactions instead of investment in education or financial assets. See, for example, Fernández et al. (2004), Fernandez and Fogli (2009), Doepke and Zilibotti (2008) and Dohmen et al. (2012).

[10]The time span of each period is not too short, and final goods are produced and used as inputs simultaneously in each period.

In turn, price of final good in location i for consumers is:

$$p_{it}^{j} = \Gamma_j \left(\sum_{\ell \in \mathcal{N}} \left(\tau_{i\ell t} \Xi_{\ell t}^{j} / Z_{\ell t}^{j} \right)^{-\theta_j} \right)^{-1/\theta_j} \tag{8}$$

where Γ_j is constant parameter. The gravity structure of regional trade characterized by (7) and (8) summarize the spatial linkage of goods.

The aggregate productivity in the local production place is increasing in employment size and evolves through the spatial spillovers:

$$Z_{it}^{j} = A_{it}^{j} \left(\sum_{n \in \mathcal{N}} L_{int}^{j} Z_{nt-1}^{j} \right)^{\rho} \left(L_{it}^{j} \right)^{\gamma_j}, \quad \text{for all } i \in \mathcal{N} \text{ and } j \in \mathcal{K} \backslash 0 \tag{9}$$

The fundamental productivity $\{A_{it}^{j}\}$ changes over time to reflect the technological change in sector j in the local economy. If $\rho = 0$, productivity increases in the size of local workers to power $\{\gamma_j\}$, which naturally arises when economies of scale exist. Suppose that $\rho > 0$. Each location benefits from other locations through workers (including stayers) who migrate from productive places of sector j. Intuitively, a large inflow of workers from productive places enhances local productivity. This is microfounded by the movement of workers who produce ideas based on the knowledge accumulated in previous places.[11] The exogenous environment may create a random difference in productivity across space through A_{it}^{j}, while employment growth and flow of workers create the self-organizing technological advancement across space.[12]

3.3 Development of Residential Stocks

Sector 0 denotes the residential structure. The structures are produced by a competitive developer sector that can convert structures over the residential land $\{T_i\}$. We let h_{it} refer to the stock of structure per unit of land in period t and $\bar{h}_i$ refer to the constant depreciation rate. The production technology of a developer sector exhibits constant return to scale. Letting l_{it}^{0} be the employment per unit of land for the development sector, the technology of developers is:

$$h_{it} = \nu_i (l_{it}^{0})^{\chi} ((1 - \bar{h}_i) h_{it-1})^{1-\chi} \tag{10}$$

Therefore, we think of development as the process of adding structure to the previous stocks by exploiting labor. The share of labor in construction is χ and the location specific productivity ν_i is unchanged over time.[13]

We consider the bidding process for developers to obtain the right to develop the place by paying rent to individuals in the location. The aggregate surplus extracted from developers through

[11] In recent, Burchardi et al. (2020) provides knowledge flow through immigration to the U.S., and Cai et al. (2022) proposes other mechanisms of knowledge diffusion through both trade and migration.

[12] When $\rho = 0$ and $\gamma_j = 1/\theta_j$, this specification is isomorphic to the new economic geography model in which the mass of firms is proportional to the mass of labor due to the fixed cost of entry and monopolistic competition. Nevertheless, in the present model, the agglomeration forces work as externalities in production but not through love of variety or extensive margins. Hence, the results of quantification are different.

[13] This is in line with Davis and Heathcote (2005) that show almost no change in productivity in the U.S. construction sector.

bidding becomes:

$$q_{it} = (1-\chi)\nu_i p^0_{it}(L^0_{it})^{\chi}((1-\bar{h}_i)H_{it-1})^{1-\chi} \tag{11}$$

Given the fixed amount of land, the bidding price for a unit of land is determined endogenously to balance the total endowment of land and the surplus from the development of land. Lastly, we make an assumption about the division rule of the surplus among the population to take the general equilibrium effects into account.

Assumption 3 *In each location, individuals hold a portfolio of land that is proportional to their labor earnings share.*

On top of the tractability, Assumption 3 does not distort the income distribution at the location since income is proportional to wage.[14]

3.4 Equilibrium and Aggregate Dynamics

This subsection describes the aggregation in the economy and defines the equilibrium. Combining individuals' choices in self-selection in (6) and the gravity structure of migration in (4) determine the spatial allocation of labor and its dynamics:

$$L^j_{it} = \sum_{n\in\mathcal{N}} \lambda^j_{int}\kappa^j_{nt}L_{nt-1}, \tag{12}$$

where L_{nt-1} is the total population of generation $t-1$ in location n. This equilibrium condition supposes that the *ex ante* indirect utility of generation t born in n is equalized and it is equal to the value of the outside option for generation t born in n to preserve the total population over generations.[15]

The market clearing conditions for final goods imply that the total value of production of sector j is:

$$X^j_{it} = \sum_{k\in\mathcal{K}\backslash 0} \beta_{kj} \sum_{n\in\mathcal{N}} \pi^k_{nit}X^k_{nt} + \sum_{k\in\mathcal{K}} \psi^k_{j|it}W^k_{it}L^k_{it}, \tag{13}$$

where, on the right-hand side, the first term is demand from intermediate producers in location i for the use of materials, and the second term is aggregate demand from individuals consump-

[14] Another way of distribution rule is that the total land rent is divided among people with equal share. Then, the income becomes $w^s_{it} + R_{it}/L_{it}$. The drawback of this specification is that the income ratio between workers in different sectors is not preserved. This feature is not convenient in the analysis of the inequality among workers. However, the definition of competitive equilibrium is not largely different from this assumption. In Caliendo et al. (2019), land is owned by a national investment fund to which all workers participate with shares taken from the data. In the present model, land is locally owned by local workers. Hence, in their case land prices do not affect the location decision, while in ours they do.

[15] Let $\mathbb{V}_{nt}$ be the value of the outside option for workers of generation t born in location n. If $V_{nt} < \mathbb{V}_{nt}$, people move to outside option and the total population of generation t is strictly lower than L_{nt-1}. If $V_{nt} = \mathbb{V}_{nt}$, we suppose that people stay in the economy and total population of generation t is equal to L_{nt-1}. When $V_{nt} > \mathbb{V}_{nt}$, potentially people in outside option enter into the economy, therefore the total population of generation t is equal to or more than L_{nt-1}. The baseline analysis supposes that $V_{nt} = \mathbb{V}_{nt}$ in equilibrium to equalize the total population of generation t to L_{nt-1}, and $\mathbb{V}_{nt}$ is determined endogenously according to (6).

tion.[16] Analogously, the market clearing condition for residential stocks is:

$$p_{it}^{0}H_{it} = \sum_{k\in\mathcal{K}} \psi_{0|it}^{k} W_{it}^{k} L_{it}^{k}. \tag{14}$$

The right-hand side is the total expenditure on housing of workers in location i and $\psi_{0|it}^{k}$ captures the different expenditure patterns of workers by their sector. The labor market of industry j in location i clear at each point of time:

$$\begin{aligned} w_{it}^{j}L_{it}^{j} &= \beta_j \sum_{n\in\mathcal{N}} \pi_{nit}^{j} X_{nt}^{j}, \\ w_{it}^{0}L_{it}^{0} &= \chi \nu_i p_{it}^{0} (L_{it}^{0})^{\chi} \big((1-\bar{h}_i)H_{it-1}\big)^{1-\chi} \end{aligned} \tag{15}$$

where β_j is the labor share of sector j in the production of intermediate goods and χ is the labor share in the development of residential stocks. To close the description of the aggregate economy, $\sum_{i\in\mathcal{N}} L_{it} = \bar{L}$ for all period t. This implies that the total population size is fixed at the national level.

We now define the equilibrium in the economy. The notations are the following: $\mathcal{F}_t$ denotes the set of time-varying fundamentals including migration costs between locations $\{D_{nit}\}$, trade costs $\{\tau_{int}\}$, exogenous productivity growth $\{A_{it}^{j}\}$, amenities $\{B_{it}^{j}\}$ and exogenous shifter of macroeconomy taste $\{\zeta_{jt}\}$, and $\bar{\mathcal{F}}$ denotes the set of time-invariant fundamentals that consist of efficiency in the development of housing $\{\nu_i\}$, re-structuring parameter $\{\bar{h}_i\}$ and endowment of land $\{T_i\}$. The initial state $\mathcal{G}_0$ includes the initial population distribution in the economy, the initial productivity $\{Z_{i0}^{j}\}$ and the initial endowment of residential structure (i.e., housing). Then, variables of interest are dynamics of ($\{\psi_{k|it}^{j}\}$, $\{\lambda_{int}\}$, $\{\kappa_{it}^{j}\}$, $\{\pi_{nit}^{j}\}$, $\{p_{it}^{j}\}$, $\{w_{it}^{j}\}$, $\{H_{it}\}$, $\{q_{it}\}$): expenditure patterns, location choice of workers, sector choice of workers, the pattern of trade, price of consumption goods and housing, wage, amount of residential structure and land rent.

Definition 1 *Given ($\mathcal{F}_t$, $\bar{\mathcal{F}}$, $\mathcal{G}_0$) and parameters, the dynamic equilibrium of the economy is characterized by endogenous sequences of: $\{\psi_{k|it}^{j}\}$ solving utility maximization, $\{\lambda_{int}\}$ determined by (4), $\{\kappa_{it}^{j}\}$ determined by (6), $\{\pi_{nit}^{j}\}$ determined by (7), $\{p_{it}^{j}\}$ that solve market clearing conditions (13) and (14), $\{w_{it}^{j}\}$ that solves labor market clearing condition (15), and $\{H_{it}\}$ and $\{q_{it}\}$ solving profit maximization of developers (10) and (11).*

The dynamic equilibrium describes the full transition of economic activities over time and space. To guarantee the uniqueness of the forward solutions, we need assumptions on parameters in the model. Intuitively, larger variation in labor mobility (ε and ϕ) and trade ($\{\theta_j\}$) and difference in expenditure patterns ($\{\mu_j\}$ and σ) across workers are related to factor mobility, while lower agglomeration forces ($\{\gamma_j\}$) prevents the concentration of workers. For the concrete discussion, we consider the special case in which $\rho = 0$ and $\chi = 1$. In this case, the dynamic equilibrium conditional on the initial state is unique when the agglomeration parameter (γ_j) is sufficiently small

[16] To simplify the discussion, the baseline analysis does not include the net export to the international market although it is straightforward to include the exogenous term of the net export.

as $\varepsilon \to \infty$, which implies homogeneous taste shocks in location choices. In contrast, the condition becomes slack as large heterogeneity in consumption across workers of different incomes (μ_j) leads to more dispersion. While the main aim of the model is a characterization of the transition process, the level of the spatial distribution of economic activities in the long run is characterized by the *stationary steady-state equilibrium* in which all aggregate variables are constant given that the exogenous time-varying factors are constant denoted by $\mathcal{F}^*$. Such steady-state equilibrium is unique if the linkages between local labor market through trade and migration create mobility of goods and workers enough not to be clustered in particular locations. The following statement summarizes theoretical augments:

Proposition 1 *(i) Given the initial state, the dynamic equilibrium of the economy with positive and finite wage $w_{it}^j \in (0, \infty)$ and employment $L_{it}^j \in (0, \infty)$ across all locations and industries exist; (ii) If $\rho = 0$ and $\chi = 1$, the sufficient condition for a unique dynamic equilibrium is given by $\gamma_j \leq \frac{\mu_j - \sigma}{\theta_k + (1-\sigma)} \left(1 + \frac{1}{\varepsilon}\right)$; (iii) Suppose that there exists a sequence of fundamentals such that $\mathcal{F}_t \to \mathcal{F}^*$. Then, the stationary steady-state equilibrium exists, and it is unique under the regularity conditions.*

The Appendix B presents details of our augments for dynamic equilibrium, and we present details in a set of conditions for the steady state in the supplementary material.

3.5 Discussion of the Assumptions and Possible Generalization

Efficient Labor. The taste shock in the industry choice in the model is crucial to characterize the aggregate equilibrium straightforwardly. It is *not* isomorphic to the model where an individual worker draws a vector of idiosyncratic labor efficiency she can supply.[17] With non-homothetic preference, its realization determines a worker's real income that is not linear in labor efficiency. Therefore, the choice probabilities of workers become different and depend on the realization of labor efficiency. This leads to complications in the characterization of the aggregate equilibrium conditions. In addition, the discussion in Section 2 helps our formulation of taste shocks.

Education. The framework can be extended to include an explicit education choice. Workers are supposed to differ in terms of not just sector and location but also education level. Consider two different education levels, for instance, graduate or non-graduate. During the first period, an individual decides whether to obtain graduate education and do so in the city of birth or other cities. Assume that she can only leave the city of birth to obtain graduate education in the junior period. Other choices are the same as in the baseline model. Introducing additional idiosyncratic factors in the net return of education can formulate the probabilities of education choice by similar representations. See the supplementary material for further discussion.

[17] Yet, the persistence of workers' skills in localities is closely related to our formulation of historical exposure effects in occupational structure. Desmet (2000) provides a theory of skill persistence as a key to explaining the different patterns of regional growth.

Infinitely Lived Workers with Perfect Foresight. Individuals work only in the second period of their life. Other approaches to seeing the dynamics entail infinitely lived workers with perfect foresight (see for example, McLaren 2017, Caliendo et al. 2019, Caliendo and Parro 2022, Kleinman et al. 2022). Comparing such an approach and the present approach, *forward* solutions of the model upon the transitory shocks are different, and therefore different transitions arise. At the expense of forward-looking choices, the present approach provides tractability to isolate the importance of migration barrier, local labor market exposure, structural transformation and externalities over space in the workers' long-run response to the common shocks. With such externalities and lower costs of labor mobility, there may exist the potential issue of self-fulfilling prophecy and multiplicity of transitions that hinges on expectations rather than the past, and it is challenging to characterize the option values by sector and geography and discuss the intergenerational link.[18] The supplementary material presents details.

4 Measures of Spatial Economy and Inequality

This section derives positive and normative analytical results regarding how structural changes shape the spatial disparity of productivity, welfare and upward mobility of workers along with the transition. Throughout this section, the fundamental amenities, sector-specific taste parameters and migration costs are assumed to be unchanged. First, Subsection 4.1 considers the transition dynamics for the total factor productivity (TFP) in local economy and its spatial variation, then discuss welfare gains and losses of workers in Subsection 4.2. Lastly, the model's simple framework speaks to the spatial difference in the degree of intergenerational mobility in Subsection 4.3.

4.1 Measured Local TFP Dynamics

The first objective is to see how exogenous shocks in the economy change the local level TFP differently by geography. Intuitively, the remoteness of the production places in the regional trade network, the pattern of migration and local labor exposure in the sectoral choice together define the geographical variation of local TFP change. Letting δ_{it}^{j} denote the local TFP of sector j in location i, the next proposition summarizes them:

Proposition 2 *Suppose that there is a common shock in the fundamental productivity in period t. The change in measured TFP in the local economy is:*

$$\frac{d\ln \delta_{it}^{j}}{d\ln A_{it}^{j}} = 1 - \frac{1}{\theta_j}\frac{d\ln \pi_{iit}^{j}}{d\ln A_{it}^{j}} + \sum_{n\in\mathcal{N}}\left(\rho\widetilde{z}_{int}^{j} + \gamma_j\widetilde{l}_{int}^{j}\right)\left(\frac{d\ln \lambda_{int}^{j}}{d\ln A_{it}^{j}} + \frac{d\ln \kappa_{nt}^{j}}{d\ln A_{it}^{j}}\right) \tag{16}$$

where $\widetilde{z}_{int}^{j} \equiv \frac{L_{int}^{j}Z_{nt-1}^{j}}{\sum_{\ell}L_{i\ell t}^{j}Z_{\ell t-1}^{j}}$ *is the contribution of location n in the baseline equilibrium; and* $\widetilde{l}_{int}^{s} \equiv \frac{L_{int}^{s}}{\sum_{\ell}L_{i\ell t}^{s}}$ *is the*

[18] This is a fundamental challenge for dynamics economic geography models. See, for example Krugman (1991), Matsuyama (1991), Ottaviano (1999), Baldwin (2001). Yet, Allen and Donaldson (2022) show that quantitative results of the model with forward-looking are similar to the present model when the discount factor is sufficiently large.

share of workers' inflow. In the steady state, the local TFP converges to:

$$\ln \delta_i^j = -\frac{1}{\theta_j} \ln \pi_{ii}^j + \sum_{n \in \mathcal{N}} \Psi_{in}^j \left(\ln A_n^s + (\gamma_s + \rho) \ln L_n^s + \rho \Delta_n^j \right) \tag{17}$$

where Ψ_{in}^j is (i, n)-th element of the matrix $\Psi^j \equiv \sum_{m=0}^{\infty} \rho^m \{\lambda_{in}^j \kappa_n^j \widetilde{l}_{in}^j\}^m$ and Δ_n^j is a small positive constant.

See the Appendix C.1 for derivation. Consider a common shock to the fundamental technology of sector j in the economy at period t. The second term in (16) reflects the gains from trade: an increase in local TFP is associated with more export to other locations. A small trade elasticity (θ_j) leads to a large variation of local TFP gains *ceteris paribus*. The third term in (16) conflates the scale effect and spillover from the in-migration of workers. A large value of scale economies (γ_j) and spillover effect (ρ) are associated with the significant variation of local TFP gains *ceteris paribus*. An increase in sectoral productivity leads workers away from the sector, and its reallocation differs by location according to the industrial specialization. Therefore, higher mobility of labor and a higher degree of industrial specialization leads to a large variation of local TFP gains.

In the steady state the first term in (17) captures the comparative advantage in trade, and the matrix $\{\Psi_{in}^j\}$ summarizes the linkages between productivity in all other locations and the local labor market.

4.2 Measure of Welfare

Next, we consider the welfare dynamics in the transition of the economy. Our interests are the spatial difference in welfare change and its decomposition into different margins in the model. To this end, V_{it} in (6) is a measure of welfare for individuals of generation t who have origin i. Then the welfare change of individuals between two consecutive generations of workers who have the same origin is given by the following proposition:

Proposition 3 *In the dynamic equilibrium, the change of welfare measure over generations $\dot{V}_{it}$ is proportional to:*

$$\prod_{s \in \mathcal{K} \setminus 0} \left(\dot{\lambda}_{iit}^s\right)^{-1/\varepsilon} \left(\dot{\kappa}_{it}^s \left(\dot{L}_{it-1}^s\right)^{-\eta}\right)^{-1/\phi} \left(\left(\dot{e}_{s|it}^s\right)^{\frac{1}{1-\sigma}} \left(\prod_j \left(\frac{\dot{w}_{it}^j}{\dot{\delta}_{it}^j} \right)^{\beta_s} \left(\dot{\pi}_{iit}^j\right)^{-\frac{1-\beta_s}{\theta_j}} \right)^{-\widetilde{\beta}_{sj}} \right)^{\widetilde{\mu}_s} \tag{18}$$

where $e_{s|it}^s$ is expenditure on sector s by workers in sector s and location i, $\widetilde{\beta}_{sj}$ is an element of matrix $(\mathbf{I} - \widetilde{\mathbf{B}})^{-1}$ with $\widetilde{\mathbf{B}} \equiv \{\beta_{sk}\}$, and $\widetilde{\mu}_s \equiv (1 - \sigma)/(\mu_s - \sigma)$.

The Appendix C.2 presents details of derivation. The first term is the change in non-migration probability with elasticity $-1/\varepsilon$. Conditional on the sector choice, $\dot{\lambda}_{iit}^s$ is expected to be declining as migration frictions are smaller, *ceteris paribus*. This term depends on the responses of labor mobility across all local labor markets to arbitrary changes in the environment and summarizes the degree of the land of opportunity for workers. When $\varepsilon \to \infty$, idiosyncratic shocks in location choice are homogeneous, and gains from migration become zero. The second term captures how flexibly workers move across sectors or how labor is specific to the sector. Greater job opportunity for workers in location i is associated with less labor specificity to the sectors in their origin. Instead, a huge distortion in the sector choice $\{\kappa_{it}^{s}\}$ implies a lower opportunity for the future location choice, and it turns out to lower welfare gain in dynamics. Given these endogenous responses, the large heterogeneity in the taste shocks across industries (small ϕ) leads to greater welfare changes as it allows the variety of industry choices during the young for workers or less labor specificity. The local labor market externalities lead to further job opportunities for sector s when the sector exhibits employment growth in the previous period.

Apart from these choice probabilities of individuals, the last part in the welfare dynamics stands for the change of real income from the consumption of tradable goods. With a non-homothetic demand system, change in demand for sector s is decomposed into the change in expenditure patterns, change of purchasing power in the local market and change in terms of trade. Comparing the non-homothetic demand and homothetic demand ($\widetilde{\mu}_s = 1$), the welfare growth to the local price change depends on the curvature of the local Engel curve. If the local Engel curve shows a relatively high slope (i.e., $\widetilde{\mu}_s > 1$), the size of welfare change and its spatial variation becomes large.

These welfare dynamics relate to the key mechanisms of reallocation of workers along with the structural transformation in the model. Large migration opportunities, job opportunities, and consumption opportunities provide an incentive for workers to move to the local labor market, and production relocates to the place in response to the productivity changes and demand shifts. The spatial linkages between local labor markets determine the distributional effects of TFP change and welfare change over time.

4.3 Implication for Upward Income Mobility

We are now in a position to discuss income mobility. We aim to understanding the relationship between spatial structural transformation and intergenerational mobility of workers – how does the next generation climb up the income ladder compared to the previous generation? The model abstracts the exact linkage between individual pairs of parents and children, and therefore there is no explicit inter-generational link between specific pair of parents among generation $t-1$ and children among generation t.

Nevertheless, the model emphasizes the importance of location choices and sector choices in shaping the geography of intergenerational mobility. In particular, for each location, the model allows us to characterize (i) the income distribution of generation t (i.e., parents) working there, and (ii) the income distribution of generation $t+1$ (i.e., children) who have the origin there. Therefore, we assess the general equilibrium relationship of income distribution between parents and children in each location.[19] We let R_{it}^{O} be the average percentile in the national income distribution for generation t working in location i, and R_{it+1}^{Y} refers to the expected percentile in the national income distribution for the next generation who are born in location i. Using these percentiles, the

[19] Note that the income distribution in the model is characterized by the probability mass function across different income levels. Income levels take $N \times (K+1)$ different values.

baseline index of intergenerational mobility for individuals in location i is:

$$M_{it+1} = R^{Y}_{it+1} / R^{O}_{it}. \tag{19}$$

The ratio between the expected income percentile of generation $t+1$ and the average income percentile of generation t, M_{it+1}, shows the expected climb up on the income ladder for individuals who have origin in location i. When location i exhibits greater land of opportunity in terms of upward income mobility for the future, $M_{i,t+1}$ returns a high value. The measure (19) becomes large when workers of generation $t+1$ sort into the industry with high wage growth and move to the location with relatively high wages and a large surplus from land. The relationship between the measure and the equilibrium of the model is summarized in the following proposition:

Proposition 4 *Define the income distribution in the whole economy Q_t such that:*

$$Q_t(W^j_{it}) = \sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{K}} f^k_{nt} \mathbf{1}[W^k_{nt} \leq W^j_{it}] \frac{L_{nt}}{\bar{L}} \equiv Q^j_{it}$$

The upward income mobility measure for generation $t+1$ in terms of average rank is:

$$M_{it+1} = \sum_{j\in\mathcal{K}} \kappa^j_{it+1} \left(\sum_{n\in\mathcal{N}} \lambda^j_{nit+1} \frac{Q_{t+1}(W^j_{nt+1})}{\sum_{k\in\mathcal{K}} f^k_{it} Q_t(W^k_{it})} \right) \tag{20}$$

The measure (20) is intuitive. It is useful to see the decomposition of this measure into the different margins in the model:

$$M_{it+1} = \sum_{j\in\mathcal{K}} \left(\underbrace{\kappa^j_{it+1}}_{\text{Job Opportunity}} \underbrace{\frac{Q^j_{it}}{\sum_{k\in\mathcal{K}} f^k_{it} Q^k_{it}}}_{\text{Local Inequality}} \underbrace{\frac{Q^j_{it+1}}{Q^j_{it}}}_{\text{Local Growth}} \underbrace{\left(\sum_{n\in\mathcal{N}} \lambda^j_{nit+1} \frac{Q^j_{nt+1}}{Q^j_{it+1}} \right)}_{\text{Spatial Mobility}} \right), \tag{21}$$

where the first term of sector choice probability reflects the job opportunity in location i for generation $t+1$. The second term is about the local income inequality for generation t as it is the relative position of workers in sector s to the local average in terms of income. The third term is the growth of the local labor market over generations represented by the change of positions in national income distribution between two generations for each industry. The last term in parenthesis captures gains from the geography of labor mobility for generation $t+1$. Thus, the variation of intergenerational mobility in geography is the consequence of the different extent of structural change and evaluates the importance of spatial economy regarding how further the young generation can climb up the income ladder.

To understand this measure more concretely, we consider the special cases. The first case supposes no geographical mobility of workers and two different sectors. Then, this measure is reduced to:

$$M_{it+1}|_{D_{ijt}\to\infty} = \sum_{j\in\mathcal{K}} \kappa^j_{it+1} \frac{Q^j_{it}}{\sum_{k\in\mathcal{K}} f^k_{it} Q^k_{it}} \frac{Q^j_{it+1}}{Q^j_{it}}. \tag{22}$$

Assume that sector j is sufficiently productive compared to k and becomes more productive in the next period. Then, $Q_{it}^{j} > Q_{it}^{k}$ and $Q_{it+1}^{j}/Q_{it}^{j} > Q_{it+1}^{k}/Q_{it}^{k}$. Then, if location i shows large income inequality if $f_{it}^{j} < f_{it}^{k}$. Suppose workers are sorting more into industry k in the next period due to persistence in their job choices. In that case, we see lower social mobility in location i compared to the case in which labor is fully adjusted to the expected growth of an industry. This is one important mechanism that relates inequality in the local economy to low social mobility there.

Another extreme case is the economy, where industries are differentiated by their locations, a lá Armington model. Then, the measure of intergenerational mobility is:

$$M_{it+1} = \sum_{n \in \mathcal{N}} \lambda_{nit+1} \frac{Q_{nt+1}}{Q_{it}} \tag{23}$$

This is the weighted average of the relative expected income ranking (Q_{nt+1}/Q_{it}) with migration patterns (λ_{nit+1}). Therefore, intergenerational mobility becomes low when the origin shows low productivity growth or high migration costs to the growing regions. This relationship relates the geography of industrial growth to the degree of intergenerational mobility. In our model, these mechanisms work together to define how the location shows high social mobility along with a geographical variation of structural transformations.

We can define alternative measures for intergenerational income mobility. As a baseline, however, we use (20) since it is robust and shows continuity over time compared to other measures.[20]

5 Model's Calibration

The goal is to quantitatively assess the extent of spatial structural change and its impact on individual consequences of welfare and inequality. To this end, we use data and model structure to estimate parameters and obtain the fundamentals of the real economy.

The model is mapped into the U.S. economy. The spatial unit of locations is the core based statistical area (CBSA). The time range is from 1980 to 2010 when there have been a considerable decline in the relative price of goods to services and an increase in real housing prices in the macroeconomy. The set of industries in the model is mapped into 18 industries. Among them, we consider the construction sector, 9 manufacturing industries, and 8 service industries. The construction sector corresponds to sector index 0 that develops the residential stock in the model. All of the sectors classified in the manufacturing sector are tradable, while one sector among service sectors, retail, is non-tradable. For CBSAs and sectors, data on employment and industry wage are from the County Business Pattern (CBP), the American Community Survey (ACS) and decennial censuses. Through the analysis, we focus on 395 CBSAs where we are able to construct these data for different periods. For each pair of CBSAs, geographical distance is computed between the reference points for the pair of most populated counties.

[20]The supplementary material discusses other measures.

Model calibration proceeds in two parts. Subsection 5.1 discusses the parameters in the model. First, we set parameters in the demand system, production technology for manufacturing and service sectors and residential stocks. Second, we exploit the gravity structure for manufacturing sectors and tradable services and determine the trade elasticity. Third, we combine the structure of the model and parameter value of migration elasticity from the literature to obtain the industry choice parameters. Fourth, we discuss the parameter choice for the economies of scale and productivity spillover.

In Subsection 5.2 we leverage the structure of the model to back out the fundamentals in the U.S. economy. This procedure is sequential, and therefore we discuss it step by step. We assume that the economy is in the stationary steady state equilibrium in the last period of 2010. Then, the structural relationships allow us to derive the fundamentals in the development of residential stocks, amenities and productivity that are consistent with the distribution of workers to be the steady state equilibrium. Then, the inversion of the equilibrium conditions leads to fundamentals in past periods. The details of data construction and technical details are in the Appendix D.

5.1 Parameters

We explain the parameters in the baseline analysis.

Demand and Production. The demand system has three parameters. We set the elasticity of substitution between different industries $\sigma = 0.40$, which ensures their complementarity. We assign the slope of the Engel curve based on the estimation from Comin et al. (2021) and set different values between two large categories of manufacturing sector and service sector. Namely, μ_k is normalized for construction sector and manufacturing sector. For service sector, we set μ_k such that $(\mu_k - \sigma)/(1-\sigma) = 1.75$, which is in the middle of estimates from Table I in Comin et al. (2021). Therefore, the expenditure share on manufacturing sectors is independent of real income, while that on service sectors increases in real income. For the rest of the parameters in the demand system, the parameters of demand shift $\{\alpha_s\}$ are chosen to match the year 2010 expenditure shares in the manufacturing and service sector.

We need input share for each industry. Using the US Bureau of Economic Analysis (BEA) table of input-output accounting, we compute these shares to match the average values during 2011-15. On the development of residential stock, the production technology exhibits the labor share equal to χ. The input-output accounting from BEA gives $\chi = 0.35$ for labor share in the construction sector on average.

Trade Elasticity. The regional trade in the model is the gravity fashion. We parametrize the impediment of trade such that trade costs between different locations are elastic function of geographical distance with elasticity ϖ_T. Then, we obtain the restricted gravity equation for the value of export from n to i. We estimate $\varpi_T \theta_k$ for manufacturing sector by using U.S. Commodity Flow Survey (CFS) in 2012. After the estimation of the gravity equation, to decompose the trade elasticity of each industry $\{\theta_k\}$ and trade cost elasticity (ϖ_T), we assume $\varpi_T = 0.125$. The value is close to the estimates in Eaton and Kortum (2002) and lower than trade cost elasticities estimated for international trade. This gives the inferred different trade elasticities by manufacturing industries that are in the range of estimates in the literature.[21] Turning to the service sector, we cannot directly observe the trade flows and we rely on the estimation by Anderson et al. (2014). Their estimates can be directly used in our definition of service sectors to pin down the trade elasticity of services. We assume the same value of trade cost elasticity as manufacturing sectors and obtain the different trade elasticity by service industries.

Migration Costs and Elasticities in Labor Supply. There are three parameters in the choice of workers and also need to characterize the migration frictions. The first parameter is the shape parameter of Fréchet distribution of the idiosyncratic shocks in location choice, which captures the elasticity of labor allocation across different locations with respect to real income.Following Fajgelbaum et al. (2019), we set $\varepsilon = 1.5$. Next, we consider the migration costs. Suppose that the bilateral migration cost is decomposed into an elastic function of bilateral distance and destination characteristics. In particular, we parametrize $\ln D_{int} = \varpi_M \ln \text{dist}_{in} + \ln F_{it}$ for migration cost from n to i. ϖ_M is positive constant and F_{it} is destination characteristics. Under this parametrization, the model derives the gravity equation of labor mobility between locations conditional on sector choice with distance elasticity $\varepsilon\varpi_M$. To estimate ϖ_M, we use American Community Survey (ACS) 5 year sample data between 2006-10 and 2011-15. In their sample, the ACS data allows us to identify the current county, previous county and industry of the worker. We extract workers in sectors of our analysis and map their locations to the CBSA level and focus on workers who moved between different CBSAs in the sample to estimate the gravity equations. Based on the estimates during different sample periods, 2006-10, 2011-15 and 2006-10, we set $\varpi_M = 0.50$.[22]

Once we have the migration elasticity and bilateral term in migration cost, we leverage the structural equations for labor mobility to calibrate the other two key parameters in the choice of individuals (η and ϕ). Given the parameters (ε, ϖ_M), the model allows us to characterize the mobility of workers in equilibrium. For each pair of values (ϕ, η), exploiting the equilibrium condition for the labor allocation (12), we uniquely determine the set of endogenous characteristics that rationalize the observed change in the distribution of workers. In turn, we can compute predicted migration flow in equilibrium, $\widehat{L}_{int}$, between any particular pair of CBSAs.

Therefore, we can define the moment conditions that argue the differences between the observed pattern of labor mobility (L_{int}^{Data}) between CBSAs and the predicted one in the model ($\widehat{L}_{int}$) are not systematically correlated to the bilateral distances between source and destination within the same range of distances. As an observation of labor mobility, we exploit Internal Revenue Service (IRS) county-to-county migration data and aggregate them to the CBSA pairs for two time

[21]See, for example, Head and Mayer (2014) and Simonovska and Waugh (2014) for international trade and Gervais and Jensen (2019) for domestic trade in the U.S.

[22]The estimates of the gravity equation are similar to the findings for intra-national migration elasticity to distance in the literature (e.g., Bryan and Morten 2019). Compared to Allen and Arkolakis (2018), estimates are small. This difference may arise from the difference in periods. For the old period, it would be large because of the higher moving cost per unit of distance.

periods, 1990-2000 and 2000-2010. Comparing the pattern of labor mobility between data and prediction in the moment conditions, we obtain the estimated value of two parameters: $\phi = 2.50$ and $\eta = 0.80$.

Productivity Spillovers. We assign the value of parameters in agglomeration economies $\{\gamma_j\}$ based on the discussion in theory. The one condition imposed on the parameter argues that the dynamic equilibrium converging to the stationary steady state equilibrium is unique when γ_j is not too large to avoid the degenerate equilibria. Since the long-run equilibrium in history does not show such a degenerate equilibrium, we use the condition to set γ_j.

As we discussed in Section 3, one of the conditions that is related to the uniqueness of the dynamic equilibrium conditional on the initial state is given by $\gamma_j \leq \frac{\mu_j - \sigma}{\theta_j + (1-\sigma)}\left(1 + \frac{1}{\varepsilon}\right)$. This condition gives the upper bound of the parameter when allowing labor mobility across locations, productivity spillover happens only locally ($\rho = 0$), and the supply of residential stocks is perfectly elastic ($\chi = 1$). In the quantification, however, we allow $\rho \neq 0$. The spillover in productivity across space through migration of workers leads to further agglomeration forces in the steady state since favorable locations attract workers while the remote places lose. Therefore, we take the conservative values that satisfy the condition with additional restriction $\varepsilon \to \infty$. This assures that the dynamic equilibrium is unique when idiosyncratic shocks for location choices are even homogeneous. This gives us the parameter values by industry such that $\gamma_j = \frac{\mu_j - \sigma}{\theta_j + (1-\sigma)}$. [23] Lastly, for the parameter of spatial spillover (ρ), we discuss it in the next subsection along with the inversion of productivity.

5.2 Calibration of Fundamentals

Next, we solve the model for the fundamentals of the economy conditional on the information about the local labor markets. This approach is formalized in the following proposition:

Proposition 5 *(i) Suppose that the economy is in a stationary steady state. Given parameters of the model and conditional on the observation of wages $\{w_i^j\}$, employment $\{L_i^j\}$ and housing prices $\{p_i^0\}$, we can solve the market clearing conditions to obtain the unique vectors of time invariant variables conflate $\{\nu_i, \bar{h}_i\}$ and unique matrix of steady state level fundamental productivity $\{Z_i^j\}$ and fundamental location attractiveness $\{\Omega_i^j\}$ that conflate $\{B_i^j, F_{it}, \zeta_j\}$.*
(ii) Given parameters of the model and time invariant variables and the sequences of wages $\{w_{it}^j\}$, employment $\{L_{it}^j\}$, we can solve the labor mobility conditions and market clearing conditions for the unique matrix of fundamental productivity $\{Z_{it}^j\}$ and fundamental location attractiveness $\{\Omega_{it}^j\}$.

The whole process is sequential, so we explain the procedure by step in the Appendix D.3. In the first step we compute the time-invariant location characteristics while assuming that the economy is in the steady state level in 2010. Then, we back out the productivity and attractiveness

[23] It is worth emphasizing that we assume that $\chi = 1$ to derive the condition. If $\chi < 1$, the supply of residential stocks becomes less elastic and a congestion force arises. Therefore, setting $\chi = 1$ keeps the conservative value for the purpose. For comparison to the existing values in empirical studies, we also refer to values in Combes et al. (2012) and Bartelme et al. (2021) in the supplementary material.

of locations that combine amenities and migration friction using the system of equations in the equilibrium. Once we obtain the productivity, we decompose the overall productivity into the exogenous part of productivity and estimate the parameter of spatial spillovers. In the next step we solve the model for the time-varying fundamentals. We match the dynamic equilibrium and observation of wage and employment for the inversion of the path of exogenous part of productivity, amenities, migration frictions and sectoral shifters.

Step #1: Model Inversion for Steady State. We first exploit the Housing Price Index (HPI) of all-transactions index across CBSAs for 2010 from Federal Housing Finance Agency (FHFA) to solve the zero profit conditions for $\widetilde{\nu}_i \equiv \nu_i(1-\bar{h}_i)^{1-\chi}$ conditional on wage $\{w_i^0\}$ and housing price $\{p_i^0\}$. Given the set of parameters in production and trade and those of preference and conditional on wage vectors and employment across locations and sectors, solving the utility maximization (3), zero profit conditions (8) and labor market clearing conditions (15) together yields a unique matrix of the equilibrium prices, price indices and productivity $\{p_i^j, P_i^k, Z_i^j\}$ that are consistent with the observation to be the equilibrium. Then, using the model structure, we invert amenities and location characteristics in the migration frictions that determine the exogenous gains for workers who choose the destination but it is unable to isolate them. Therefore we let $\Omega_i^j \equiv (B_i^j/F_i)\zeta_j^{1/\phi}$ conflate these fundamentals and given the matrix of wages and employment, the labor mobility conditions (12) are inverted to find the unique matrix of $\{\Omega_i^j\}$ in the steady state. This inversion also allows us to compute the inferred probabilities of location choice for workers $\{\hat{\lambda}_{in}^j\}$ and the probabilities of industry choice $\{\hat{\kappa}_n^j\}$ respectively.

Step #2: Decomposition of Productivity. The model inversion yields the predicted labor mobility $\{\hat{L}_{in}^j\}$ in the steady state. Together with the inverted productivity $\{Z_i^j\}$ and conditional on the employment data $\{L_i^j\}$ and parameters $\{\gamma_j\}$, it is able to use (9) to compute the fundamental productivity $\{A_i^j\}$ for any particular value of parameter ρ. To estimate ρ, we consider the following moment conditions:

$$\mathbb{E}\left[\left(\ln A_i^j - \frac{1}{N}\sum_n \ln A_n^j - \frac{1}{S}\sum_k \ln A_i^k\right) \times \mathbb{I}_a\right] = 0, \quad a \in \Pi_1^A, \Pi_2^A, \cdots, \Pi_O^A \tag{24}$$

where $\mathbb{I}_a$ is an indicator that the location i and sector j is in the group of a. The group is defined by the labor market potential for each location and sector. Namely, for location i and sector j, we compute the measure $\sum_{n\neq i}(\text{dist}_{ni})^{-\varepsilon\varpi_M} L_n^j$ and we order locations and sectors by this measure to define 20 groups by 5 percentile of the measure. The moment condition assumes that the location and industry specific fundamental productivity after eliminating the sector-level and location-level averages is not systematically related to the labor market access. We use (24) and obtain $\hat{\rho} = 0.0284$.

Step #3: Dynamics of Fundamentals. After defining steady-state fundamentals, we compute the change in fundamental productivity and location attractiveness for 2000-2010, 1990-2000, and

1980-1990. We suppose that the economy reached the steady state equilibrium in 2010 and compute the change of these fundamentals in the past.

We compute the residential stock and their prices in the past conditional on the current observations. Implementing parameters in production technology of residential structure (χ), observed wage and employment in the construction sector and location fundamentals ($\{\widetilde{\nu}_i\}$) into the dynamics of production of residential stocks and market clearing conditions, it gives the path of $\{p^0_{i,t-1}, H_{i,t-1}, R_{i,t-1}\}$ in the dynamic equilibrium that are not directly observable. The HPI has limited data on prices for CBSAs in 1990 and 1980 that can gauge the inversion.[24] Then, we compute the change in productivity over periods $\{Z^j_{it}\}$ such that wage and employment in the past are consistent with the dynamic equilibrium. We solve the static equation for the aggregate price index and use the market clearing condition to obtain the productivity change.

The forward equations in the model are exploited for computing the path of location attractiveness. Conditional on the observation about employment $\{L^j_{it}\}$ and income and aggregate price index constructed by the model, the labor mobility conditions (12) are inverted for the location and sector specific adjusted amenities $\{\Omega^j_{it}\}$ in each period and we are able to compute the two probabilities of workers' choice $\{\lambda^j_{int}\}$ and $\{\kappa^j_{nt}\}$ predicted by the model. Lastly, we compute the development of fundamental productivity in an analogous way to the second step. The overall productivity of two consecutive periods $\{Z^j_{it}\}$, employment $\{L^j_{it}\}$ and labor mobility $\{L^j_{int}\}$ give unique matrix of fundamental productivity $\{A^j_{it}\}$ that is consistent with the dynamic equilibrium. For the initial period we set $A^j_{it} = Z^j_{it}$ in 1980.

6 Quantitative Analysis

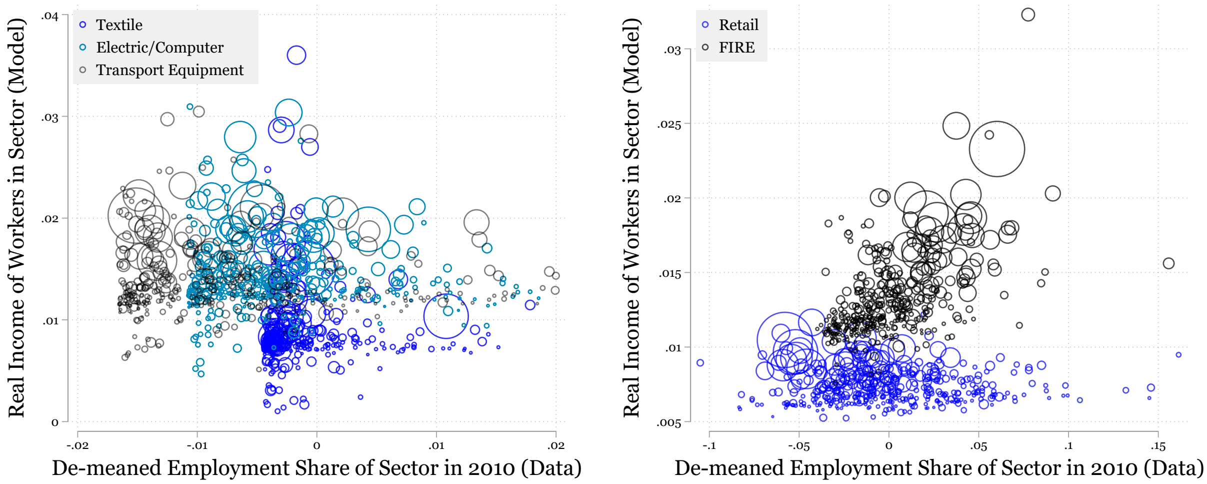
Having an inversion of the model to obtain the fundamentals in the economy and estimated parameters, we assess the role of these fundamentals and analyze the dynamics of TFP, welfare and upward mobility across CBSAs in the U.S. discussed in Section 4. We first see the role of industry and location specific amenities and derive the measured TFP. Next, we examine the disparities in welfare between two generations and assess the different margins in welfare dynamics. Lastly, we explain how the model-derived measure of intergenerational income mobility exhibits spatial variation and investigate its relationship to the underlying mechanisms in general equilibrium.

Amenities. Figure 5 shows the relationship between the real income of workers and employment share for different industries in 2010. The vertical axis is the real income of workers in any particular industry in each CBSA $\{\mathcal{W}^s_{i,t}\}$ derived using the calibrated income and nonhomothetic price index in the equilibrium relationship. The horizontal axis shows the de-meaned employment share of each industry in CBSA.

The left-hand panel 5a displays three industries in the manufacturing sector. The employment share exhibits large variation relative to real income, and the pattern is different across indus-

[24] The supplementary material presents the comparison between prices across CBSAs predicted by the model and the limited data for 1980 and 1990.

Figure 5: Real income and Employment



(a) Manufacturing **(b)** Service

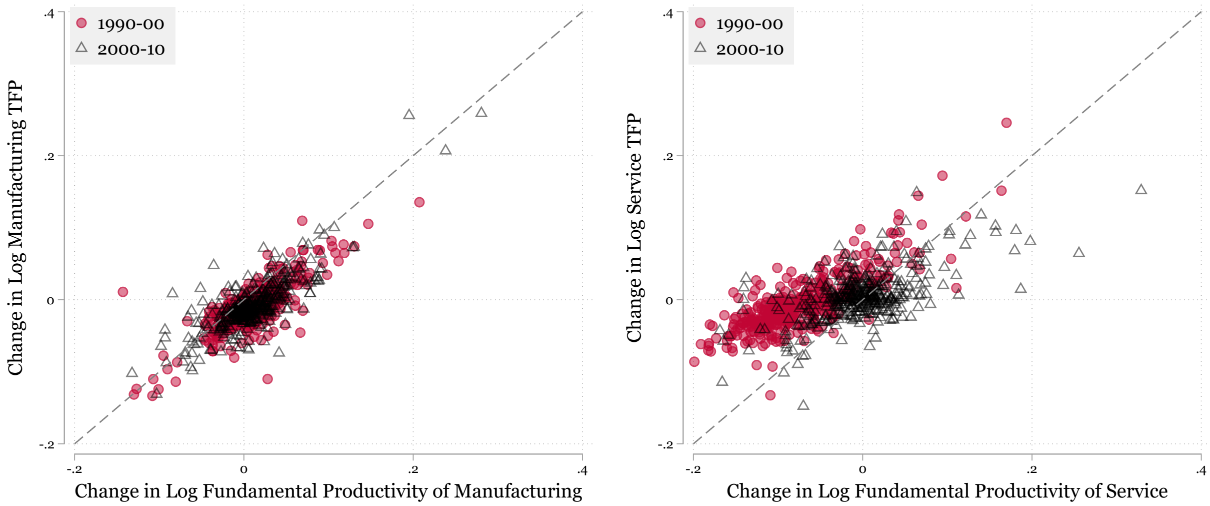
Note: The employment share of each industry is de-meaned by the average employment share across 395 CBSAs. Each circle represents the size of total employment in 2010 for CBSAs. The real income of workers is computed in the model.

tries. This confirms that there exist industry-specific amenities for workers. The right-hand panel 5b shows two distinctive industries – finance, insurance and real estate (FIRE) and retail among the services sector. For FIRE, a large employment share is associated with higher real income for workers. In contrast, the retail industry exhibits the importance of amenities to explain the spatial variation of workers. These results are consistent with industry and location specific amenities for workers' location choices and such amenities are crucial to explaining the spatial variation of employment shifts. We also confirm the relationship between the average level of amenities and the size of employment in CBSA is stable over time, suggesting the importance of location fundamentals for the persistence in the aggregate size of employment in CBSA. See the supplementary material.

Productivity. As we discussed in Proposition 2, we are able to compute measured TFP for each CBSA and industry given overall productivity $\{Z^j_{it}\}$ and trade probabilities $\{\pi^j_{iit}\}$. We find distinctive dynamics of the spatial distribution of measured TFP by industry.[25] Having measured TFP of each industry, we compute the aggregate TFP for the aggregate sectors where we compute weighted TFP by using the value of the output of industries as weights. In an analogous way, we can compute aggregated fundamental productivity. Figure 6 shows the relationship between change in aggregate sector level TFP and fundamental productivity for the manufacturing and services sector. This corresponds to the implication in Proposition 2. In the left-hand panel, changes in TFP and fundamental productivity for the manufacturing sector exhibit a similar pattern. In contrast, changes in TFP of the services sector show large values relative to the fundamental changes. This implies that TFP growth in the services sector over these periods is driven by the endogenous mechanisms of labor reallocation and productivity spillovers.

[25]These spatial distributions are in the supplementary material.

Figure 6: Change in TFP and Fundamental Productivity for Manufacturing and Service



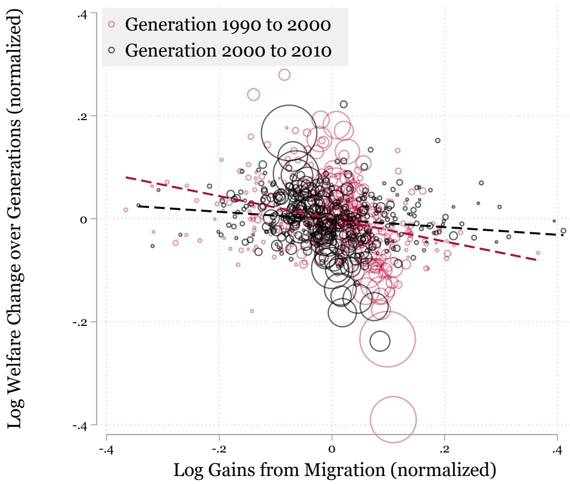
(a) Manufacturing **(b)** Service

Note: These figures show the change in log of fundamental productivity for aggregate sector and the change in log of TFP for aggregate sector.

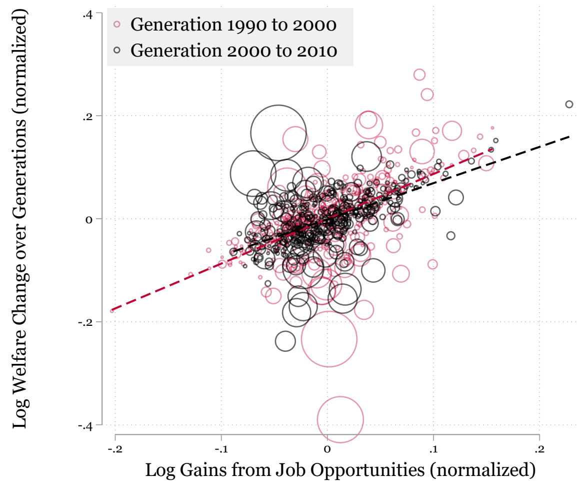
Welfare. We quantitatively evaluate the welfare dynamics discussed in Proposition 3. In sum, the welfare gains between generations t and $t-1$ can be decomposed into three different terms: first, gains from labor mobility across space ($\prod_j(\dot{\lambda}_{iit}^j)^{-1/\varepsilon}$); second, gains from job opportunities in the local labor market ($\prod_j(\dot{\kappa}_{it}^j)^{-1/\phi}(\dot{L}_{it-1}^j)^{\eta/\phi}$); third, local gains from consumption and amenities. Figure 7 presents this relationship for U.S. CBSAs.

In the first panel (a), higher gains from migration are associated with small welfare differences. The logic is clear. Conditional on industry choice and growth of real income, an increase in the probability of staying in the original location requires higher welfare gains for individuals who stay in the local labor market. Comparing the two periods, the elasticity of welfare difference to gains of migration becomes small. This is consistent with the recent decline of the migration rate in the U.S. economy. The second panel (b) shows the positive relationship between job opportunities in the local labor market and welfare. Individuals gain from the labor specificity in relatively small local labor markets. In these CBSAs, the specialization of workers into a particular industry in a growing sector leads to significant welfare differences over generations. The positive relationship is steady for these two periods. The third panel (c) exhibits the positive relationship between the change in real income adjusted with amenities and welfare differences. The change in average real income shows large variation and the role of real income disparity in the welfare change is large in the early period. The smaller elasticity of welfare differences to gains of migration and growth in the real income account for a decline of welfare differences over periods, while the gains of job opportunities account for the persistence in local labor market adjustment. These three margins are quantitatively consistent with the theoretical implications.

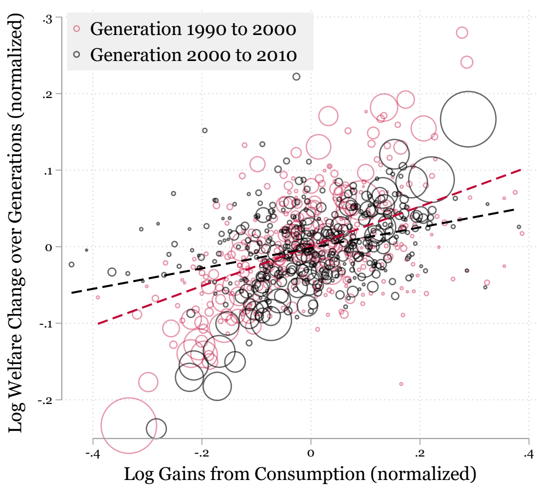
Figure 7: Welfare Differences



(a) Migration



(b) Job opportunity



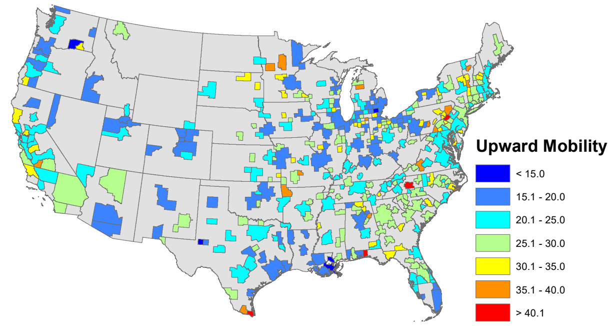
(c) Consumption

Note: These figures show the different margins in welfare differences for CBSAs. Each circle represents the employment size of CBSA in the baseline year (i.e., employment size in 1990 for the blue circle). All variables are normalized by their means.

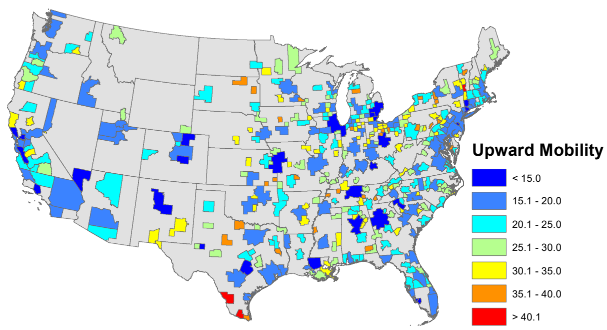
Income Mobility. The final objectives in this section are worker inequality and upward income mobility. We compute normalized measure based on M_{it+1} defined in Proposition 4. Specifically, we let $\widetilde{M}_{it+1} = (M_{it+1}/\bar{M}_{t+1}) \times 25$ where $\bar{M}_{t+1}$ is average of M_{it+1} in the economy. Intuitively, this measure gives an expected rank of individuals in CBSA i when their previous generations are in the 25 percentile in the income distribution in the economy.[26] Figure 8 display the measure for different generations. We find a considerable variation in upward mobility. For the first generation who worked in 1990, central cities in the region show relatively higher upward mobility. In later periods, upward mobility becomes lower on average. Given this spatial variation, we consider the relation of upward mobility to the underlying mechanisms in equilibrium.

[26] See the Appendix E for further discussion about the measure and relation to measures in the empirical literature.

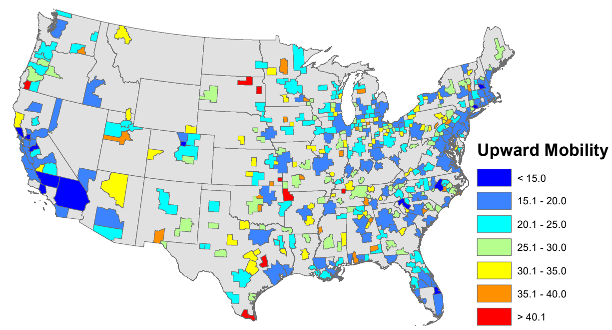
Figure 8: Geography of Upward Mobility



(a) Generation 1990



(b) Generation 2000



(c) Generation 2010

Recalling (21), the measure of upward income mobility can be written as:

$$\widetilde{M}_{it+1} \propto \sum_{j \in \mathcal{K}} \underbrace{LL^{j}_{it+1}}_{\frac{Q^{j}_{it}}{\sum_k f^{k}_{it} Q^{k}_{it}} \frac{Q^{j}_{it+1}}{Q^{j}_{it}}} \times \underbrace{ISM^{j}_{it+1}}_{\kappa^{j}_{it+1}} \times \underbrace{GLM^{j}_{it+1}}_{\sum_n \lambda^{j}_{nit+1} Q^{j}_{nt+1} / Q^{j}_{it+1}}$$

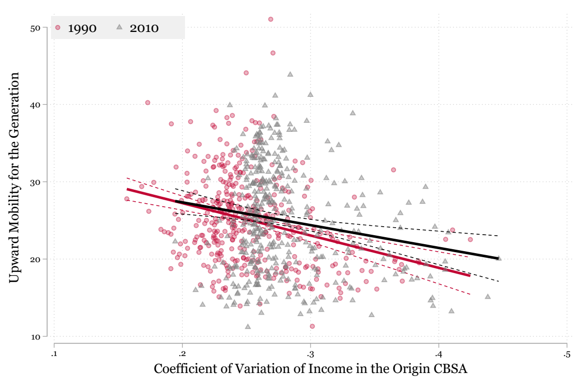
where LL^{j}_{it+1} captures the inequality in the local labor market in period t and local economic growth, ISM_{it+1} is patterns of industry choice and GLM^{j}_{it+1} is the geographical labor mobility. Figure 9 present these margins.

The first panel (a) displays the relationship between upward mobility and local inequality for two generations. We use the coefficient of variation in income within CBSA as a measure of income inequality. The vertical axis is the upward mobility measures for generations 1990 and 2010, and the horizontal axis is inequality in CBSA in 1980 and 2000, respectively. We find a negative relationship: individuals from CBSAs with large income inequality among workers are likely to experience lower upward mobility. This is related to the *Great Gatsby curve* in the U.S., showing the negative relationships between local inequality and upward mobility. Theoretically, this arises from the specialization and wage disparity in the local labor market, leading to less opportunity in the choice of industry for the next generation.

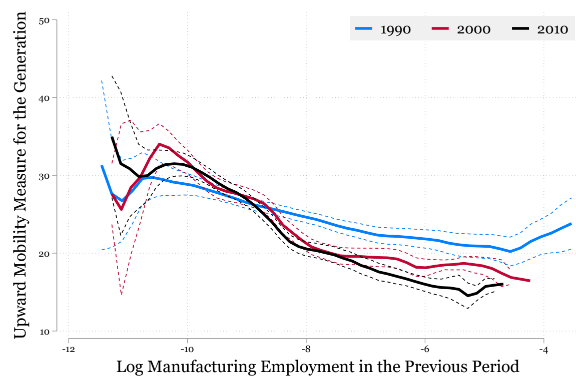
The second panel (b) shows the structural transformation and upward mobility. This implies that structural transformation lowers the upward mobility of individuals. This accounts for the part of LL^{j}_{it+1} where specialization in manufacturing leads to less growth. In the third panel (c), we consider the land of opportunities for individuals that are related to intersectoral mobility.

The horizontal axis is an expected utility from industry choice for individuals in CBSAs: large values correspond to the land of opportunities for the future. Therefore, such CBSAs exhibit high upward mobility. Over generations, the relationship becomes more robust. This confirms that the disparity in the land of opportunities drives an increase in the spatial variation of upward mobility. The last panel (d) describes the role of labor mobility across CBSAs that is related to GLM^{j}_{it+1}. The horizontal axis is the probability of non-migration for individuals from the CBSAs. Intuitively, the low mobility of workers in geography predicts less possibility of climbing up the location ladder *ceteris paribus*. As predicted in theory, a high probability of staying in origin is associated with low intergenerational income mobility. This is consistent with the decline of upward mobility along with a lower migration rate in the U.S. economy during the last decades.

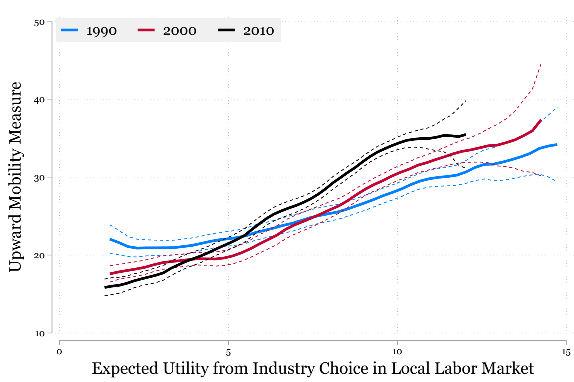
Figure 9: Intergenerational Income Mobility



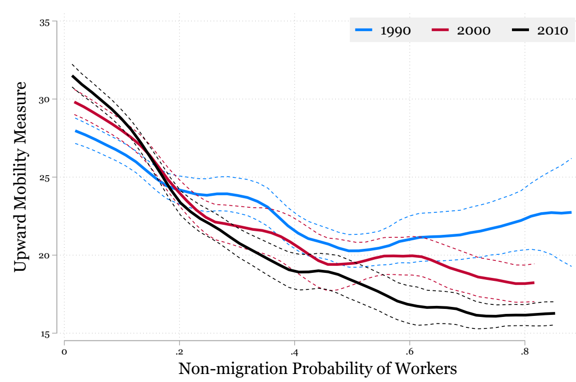
(a) Local inequality



(b) Employment



(c) Opportunity of Industry Choice



(d) Geographical Mobility

Note: These figures show the relationship between the measure of intergenerational income mobility and relevant measures. Panel (a) shows the relationship between the measure of upward income mobility for generations 1990 and 2000 to the inequality in the local labor market in the period 1980 and 1990 measured by the coefficient of variation. Each marker shows CBSA and red (black) solid line is a fitted line, and dash lines are 95% confidence intervals. Panels (b), (c) and (d) report the polynomial fitted line for CBSAs. Dash lines are 95% confidence intervals. Panel (b) shows the relationship between the upward income mobility of three different generations (1990, 2000 and 2010) to the log of manufacturing employment in 1980, 1990 and 2000, respectively. Panel (c) shows the relationship between upward income mobility and individuals' expected utility from industry choice in each CBSA for generations 1990, 2000 and 2010. Panel (d) displays the relationship between upward income mobility to the probability that individuals stay in the CBSA for three generations, 1990, 2000 and 2010.

7 Counterfactual Experiments

Armed with the data and parameters calibrated above, we undertake counterfactual experiments. In the first subsection we consider counterfactuals to understand the role of fundamental productivity and amenities in shaping structural transformation, welfare and intergenerational income mobility. In particular the objective of undertaking counterfactuals is to understand the quantitative importance of these fundamentals in explaining the spatial heterogeneity of workers' location and industry choices and how the changes in workers' mobility determine their welfare gains relative to the previous generation and their position on the income ladder. In the second subsection we undertake counterfactuals for evaluating the role of two key mechanisms in our theory - non-homothetic preference and historical exposure effects in occupational structure. The motivation for these counterfactuals is to understand the role of these underlying mechanisms of structural transformation in explaining the equilibrium allocation and workers' income mobility. In the counterfactual experiments the economy starts from the actual equilibrium observed in the data in 1980 and we implement the changes in the fundamentals to solve the counterfactual equilibrium.[27]

7.1 Shocks to Fundamentals in the U.S. Economy

Productivity shock. We undertake the first counterfactual where the fundamental productivity of the manufacturing sector $\{A_{it}^{j}\}_{j\in\text{Manufacture}}$ is dropped by 10 percent in 1990 relative to the observed level and fixed at the level for the later periods, 2000 and 2010. In the present model, a uniform shock to the fundamental productivity has nonlinear effects across locations. Consider the negative shock to fundamental productivity in the manufacturing sector in the early period when the inverted fundamental productivity grows. It directly lowers TFP of the manufacturing sector and workers are less likely to sort into the service sector since labor demand in the manufacturing sector increases. However, the present model has additional channels to amplify the general equilibrium effects. First, changes in income lead to demand shifts of workers due to non-homothetic preference, therefore creating a feedback loop in the goods market. Second, the exposure effect in the local labor market causes frictions in the workers' adjustment. These effects play out across space, leading to different rates of structural transformation across locations.

Panel A of Table 3 reports the results for the counterfactual about the TFP changes and structural changes in terms of employment share. The first row shows the negative impact on the manufacturing sector TFP. In 1990, it shows 5.7 percent lower than the baseline economy on average. Since the TFP is determined by both fundamental productivity and endogenous mechanisms through labor mobility (Proposition 2), the absolute effect is less than 10 percent, and it implies that the workers' adjustment mitigates the negative shock on average. More interestingly, the negative effect becomes smaller over time. This implies that the negative impact of fundamental

[27] The uniqueness of the dynamic equilibrium is not guaranteed in the presence of spillovers in productivity and intersectoral linkages in production. Therefore, we compute the counterfactual equilibrium with the observed equilibrium as a starting point and run the model with a small perturbation of the initial equilibrium to assess the local uniqueness of the counterfactual equilibrium.

productivity shocks in the initial period can be faded out through workers' mobility over generations. We also find an increase in the variation of the negative effect over time, implying large heterogeneity in adopting the negative shocks across CBSAs. The second row in panel A shows the difference in the employment share of services to the baseline economy. When turning off the technological progress in the manufacturing sector, we see a significant drop in the employment share of services. This happens for two reasons. The first channel is the traditional effect of factor mobility across sectors. The second channel is an additional impact of demand-driven structural changes. When we abstract the exogenous fundamental productivity growth, the real income of workers becomes low and the expenditure shift from goods (manufacturing and housing) to services is slowed down. Therefore, it further prevents the labor shift to services.

Figure 10 presents the welfare effects and change in intergenerational income mobility across 395 CBSAs. Panel (a) displays the variation of welfare effects across CBSAs. For the welfare difference between generation 1990 and 2000, the CBSAs with welfare losses in the baseline show further welfare losses in the counterfactual. The technological progress in the manufacturing sector and structural transformation benefit these CBSAs in the baseline economy. In Figure 10 Panel (b), (c) and (d) displays the distribution of the upward income mobility across CBSAs for different generations. An important takeaway from the first generation, in Panel (b), is that the productivity shock in the manufacturing sector leads to a large variation of upward income mobility for the generation 1990. Once the productivity of the manufacturing sector is fixed after 1990, Panels (c) and (d) show less variation of upward mobility. For the first generation, the average impact is relatively small since the 10 percent decline in productivity for all CBSAs does not alter the location choice of workers much, and it turns out to be a smaller effect. However, the generations of 2000 and 2010 show higher upward mobility on average. For generation 2000, individuals experience around 5.2 percent increase in upward income mobility compared to the baseline economy on average, and the gain becomes larger for generation 2010, which is around 7 percent. The logic for this result is the following. When exogenous productivity growth is absent, the endogenous spillover in productivity becomes salient, and workers sort into the place with agglomeration. In addition, as we see in welfare results, a variation of real income growth creates workers' mobility both across locations and sectors. Together with these endogenous responses of workers, we see higher upward mobility on average, but with large variation in its gain. The variation in the change of intergenerational income mobility becomes significant over time.

Role of Heterogeneity in Amenities and Migration Barriers. The second experiment undertakes the counterfactuals for the fundamental location characteristics in amenities. By construction, the variation of overall amenities across space includes both the variation of fundamental benefit $\{B_{it}^j\}$ and migration barrier $\{F_{it}\}$. We investigate the role of differences in fundamental amenities across CBSAs. To this end, we perform the counterfactual in which overall amenities develop at the same rate across all CBSAs given any particular industry.[28]

[28] As another counterfactual about the migration barrier, we set a 10 percent lower migration barrier for top CBSAs. We define the top 50 CBSAs based on the total employment size in 1980, selecting them for the counterfactual exper-

Table 3: Counterfactual Experiments: Change in Manufacturing TFP and Service Employment Share

Counterfactual Exercises	1990			2000			2010		
	Mean	25 prc	75 prc	Mean	25 prc	75 prc	Mean	25 prc	75 prc
Panel A. ***Low productivity in all manufacturing industries***									
TFP of manufacturing sector	-5.71	-7.54	-3.85	-3.69	-6.22	-1.32	-1.29	-4.44	1.88
Service employment share	-15.23	-18.87	-11.42	-22.16	-27.28	-17.58	-28.31	-34.00	-23.01
Panel B. ***Uniform changes in amenities across CBSAs***									
TFP of manufacturing sector	8.28	4.41	11.61	13.22	8.61	17.37	20.28	14.04	23.14
Service employment share	-10.86	-16.43	-5.82	-15.19	-21.35	-9.14	-15.01	-20.89	-9.24
Panel C. ***Homothetic preference***									
TFP of manufacturing sector	1.40	-0.84	3.82	2.82	0.91	5.22	5.13	2.79	7.55
Service employment share	2.39	-0.20	5.08	-1.13	-4.25	2.05	-8.44	-11.38	-5.35
Panel D. ***No exposure effects in job choices in formative years***									
TFP of manufacturing sector	4.13	1.89	6.45	7.38	5.58	9.32	10.60	8.69	12.82
Service employment share	-14.14	-17.38	-11.28	-20.91	-23.75	-18.05	-25.34	-28.47	-22.11

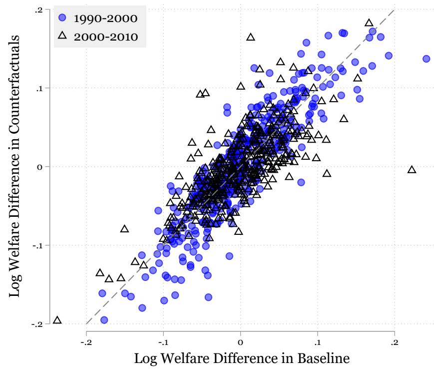
Note: For each counterfactual scenario, we report the percentage change of aggregate TFP in the manufacturing sector and the change of employment shares in the service sector from the baseline economy. For each year, 1990, 2000 and 2010, we show the mean, 25 percentile and 75 percentile values of changes across 395 CBSAs in the U.S. economy. Units of all entries are percentages. Panel A reports the results of counterfactual exercises about productivity changes when fundamental productivity of all manufacturing industries dropped by 10 percent in 1990 and is unchanged later. Panel B is the counterfactual that overall amenities are uniform across locations: we compute the geometric mean of overall amenities across CBSAs for workers in each sector, and we implement the value for all locations in each period. Panel C reports the results of the counterfactual when we consider the homothetic preference of workers. In Panel D we undertake the counterfactual when there are no historical exposure effects in job choices ($\eta = 0$).

The results are reported in Panel B in Table 3. We find this experiment benefits the TFP growth of the manufacturing sector. Once we turn off the difference in fundamental amenities among CBSAs, we predict around an 8.3 percent increase in manufacturing sector TFP on average in 1990, and it becomes 20.3 percent in 2010. This significant increase in TFP of the manufacturing sector leads to a lower degree of structural transformation since relatively high wages in manufacturing industries lead workers to sort into the manufacturing sector when any differences in amenities are absent.

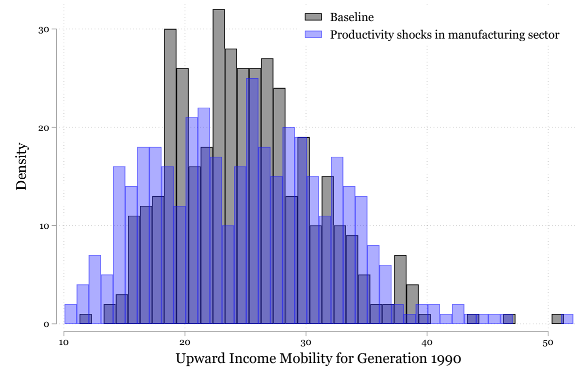
Figure 11 presents the welfare effects and change in intergenerational income mobility for this counterfactual experiment. The welfare changes are larger than the baseline economy by 2.8 percent for the generations 1990 and 2000, and it is 0.3 percent for generations 2000 and 2010. We also find substantial positive effects on intergenerational income mobility. The measure of upward mobility becomes 9.2 percent higher for those in generation 2000 and 10.8 percent higher for generation 2010 on average. However, endogenous agglomeration of industries and ex-ante distribution of workers keep such gains substantially different across space. In Panel (a), the spatial

iments. Given that most migration occurs from small towns or cities to large cities, this counterfactual is of interest to consider whether such directed migration is important to explain the variation of structural change, welfare and upward mobility. The results are in the supplementary material.

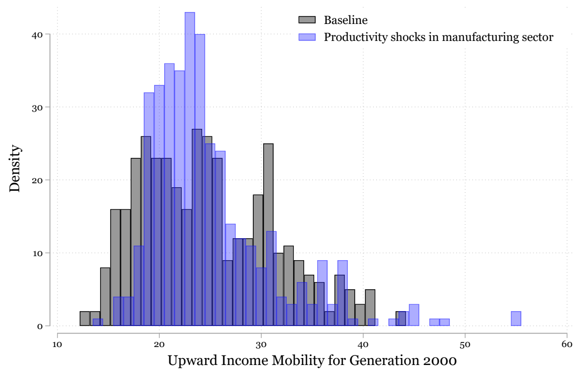
Figure 10: Welfare Effects and Intergenerational Income Mobility for the Productivity Shocks in Manufacturing Sector



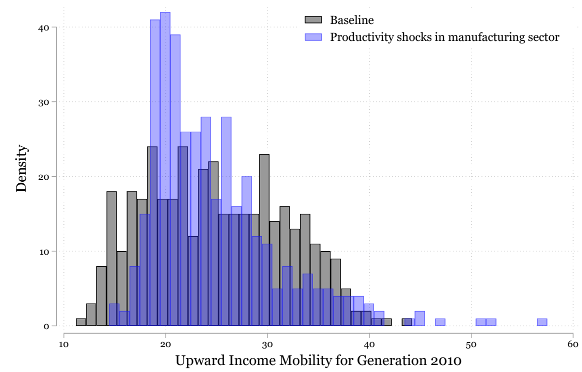
(a) Welfare effects



(b) Upward Income Mobility for Generation 1990



(c) Upward Income Mobility for Generation 2000

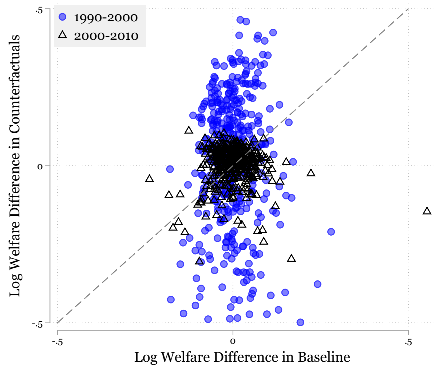


(d) Upward Income Mobility for Generation 2010

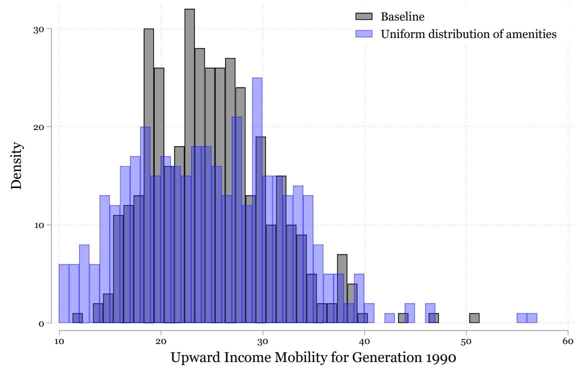
Note: These figures show the results for welfare and intergenerational income mobility for the counterfactual when fundamental productivity of all manufacturing industries is dropped by 10 percent in 1990 and fixed over time. Panel (a) shows the welfare difference for the baseline and the counterfactual between two generations, $d \ln V_{it}$. Blue dots (black triangles) show the welfare differences between generations 1990 and 2000 (2000 and 2010), respectively. In panels (b), (c) and (d), we report the distribution of upward income mobility for three different generations, generations 1990, 2000 and 2010. In each panel, gray bars show the distribution of the upward income mobility measure across CBSAs in the baseline, and the blue bars show that for the counterfactual economy.

variation in welfare differences between generations 1990 and 2000 is magnified in the counterfactual. Intuitively, equalizing amenities allows the first generation to change their location choices such that they move to productive and high real income places. This magnifies the differences in such gains among CBSAs, and, therefore, more spatial inequality in welfare gains. For the generations 2000 and 2010, the spatial variation of such gains becomes small since workers' location choices show the path dependency for each industry. Panel (b), (c) and (d) shows that the upward income mobility for generation 1990 exhibits a larger variation in the counterfactual than the baseline, while the negative impact on average. For other generations, the distribution becomes small in the counterfactual since the spatial variation in the labor mobility is less relative to the baseline once the geographical distribution of workers shows persistence after the change in the early period.

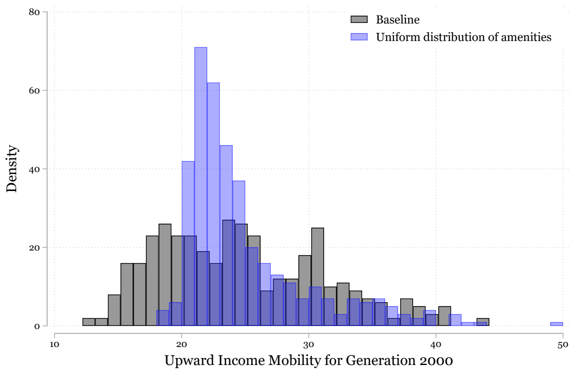
Figure 11: Welfare Effects and Intergenerational Income Mobility for the Uniform Distribution of Amenities



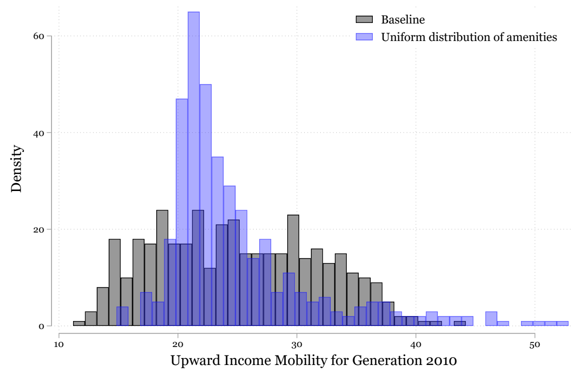
(a) Welfare effects



(b) Upward Income Mobility for Generation 1990



(c) Upward Income Mobility for Generation 2000



(d) Upward Income Mobility for Generation 2010

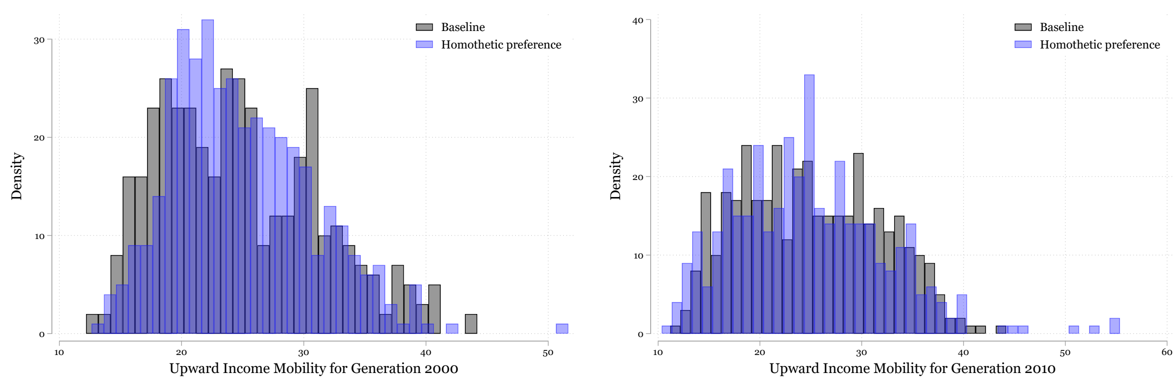
Note: These figures show the results for welfare and intergenerational income mobility for the counterfactual when overall amenities become uniform across CBSAs for given industry choices. Panel (a) shows the welfare difference for the baseline and the counterfactual between two generations, $d \ln V_{it}$. Blue dots (black triangles) show the welfare differences between generations 1990 and 2000 (2000 and 2010), respectively. In panels (b), (c) and (d), we report the distribution of upward income mobility for three different generations, generations 1990, 2000 and 2010. In each panel, gray bars show the distribution of the upward income mobility measure across CBSAs in the baseline, and the blue bars show that for the counterfactual economy.

7.2 Exploring the Role of Underlying Mechanisms of Structural Transformation

Role of Non-homothetic Preference. We now quantify the role of non-homothetic preferences as a driver of differential rate of structural transformation and how it is related to intergenerational income mobility. We solve the model for the counterfactual equilibrium when we set $\mu_j = 1$ in demand (2) for all industries while using fundamentals from our calibration. Intuitively, without non-homothetic demand, an increase in real income does not directly affect expenditure shift from goods to services, and therefore structural transformation slows down. Such a pattern of structural transformation keeps a higher TFP in the manufacturing sector compared to the baseline since more employment in manufacturing industries enhances their TFP. Panel C in Table 3 reports the impact on TFP of the manufacturing sector and employment share in services across locations. We find higher TFP in the manufacturing industries and the effects become more significant over time. The gains in TFP of the manufacturing sector are along with the lower degree of structural transformation. Employment share in services becomes 1.1 percent lower in 2000 on average and 8.4 percent lower in 2010 across CBSAs. These results are suggestive of the important role of non-homothetic demand system as an underlying driver of structural transformation and its variation across space.

Next, we turn to intergenerational income mobility. In Figure 12 we display the variation of the measure of intergenerational income mobility when we consider homothetic preference. On average, the degree of intergenerational mobility becomes high: 2.6 percent higher relative to the baseline for generation 2000 and 1.2 percent higher relative to the baseline for generation 2010. When the preference is homothetic, spatial variation in real income becomes smaller since an additional channel through the worker-specific price index is absent. Lower rate of structural transformation and less variation in real income in the counterfactual economy benefit manufacturing locations in terms of wage increase relative to the baseline economy. Yet, these effects become smaller over time when the slow structural transformation continues. The variation in amenities across locations and the increase in prices of service industries together create the dispersion force for workers, which regains the variation of workers' mobility. The main takeaway from this counterfactual for homothetic preference is that the demand-driven structural transformation matters in explaining the variation of TFP growth and creating a disparity in intergenerational income mobility over time, even if we take into account exogenous productivity and amenities.

Figure 12: Intergenerational Income Mobility for Homothetic Preference



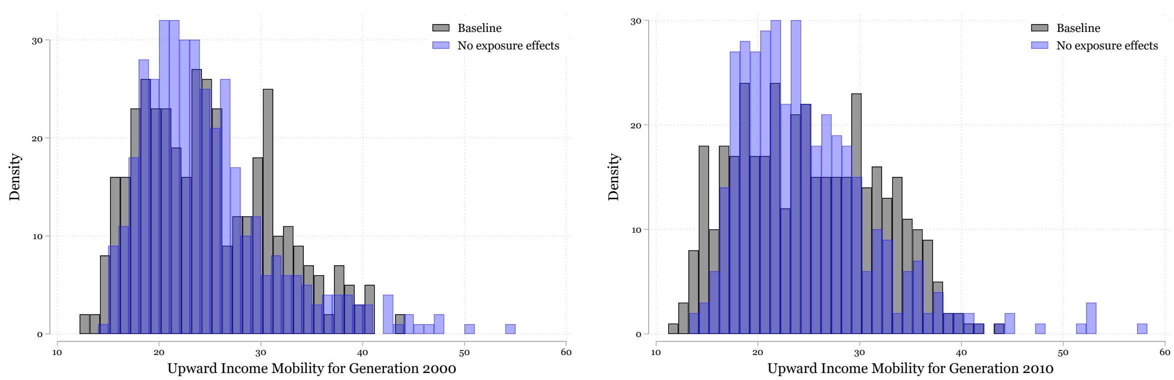
(a) Upward Income Mobility for Generation 2000 **(b)** Upward Income Mobility for Generation 2010

Note: These figures show the results for intergenerational income mobility for the counterfactual when we impose a homothetic demand system. Panel (a) and (b) show the distribution of upward income mobility for two different generations, generations 2000 and 2010. In each panel, gray bars show the distribution of the upward income mobility measure across CBSAs in the baseline, and the blue bars show that for the counterfactual economy.

Role of Historical Exposure Effects. A key parameter in our theory is persistence in job choices. We are interested in understanding how this parameter affects workers' intergenerational income mobility and the pace of structural transformation. To this end, we solve the model for the counterfactual equilibrium by imposing the parameter $\eta = 0$: the historical exposure effects in job choices during formative years of workers are absent. This implies that the probabilities that an individual worker chooses any particular industry depend on the expected utility but not the employment composition of the previous generation.

In Panel D of Table 3 we explore how such persistence in job choices in the local economy is important to drive structural transformation. We find that removing the exposure effects increases TFP of the manufacturing sector and slows structural transformation. In 1990, employment share in services is reduced by 14 percent on average across CBSAs and the effect is pronounced in the later period. This result shows that the historical exposure effects drive the sustained deindustrialization in most U.S. cities. In turn, TFP of the manufacturing sector becomes high in the counterfactual. The reason is twofold. First, more employment in manufacturing industries increases TFP through the scale effects. In addition, when there are no exposure effects in workers' job choices, mobility between industries and locations is determined by productivity differences. Workers anticipate future general equilibrium effects in wages and sort into productive places, leading to productivity spillover through migration. Therefore, locations with high productivity in the manufacturing sector improve TFP further.

Figure 13: Intergenerational Income Mobility for No Exposure Effects



(a) Upward Income Mobility for Generation 2000

(b) Upward Income Mobility for Generation 2010

Note: These figures show the results for intergenerational income mobility for the counterfactual when we assume that there are no historical exposure effects. Panel (a) and (b) show the distribution of upward income mobility for two different generations, generations 2000 and 2010. In each panel, gray bars show the distribution of the upward income mobility measure across CBSAs in the baseline, and the blue bars show that for the counterfactual economy.

Lastly, Figure 13 shows the degree of upward mobility in the counterfactual. As we can see in the figures for two generations, locations with low intergenerational income mobility in the baseline improve their degree when exposure effects in job choices are absent. On average across CBSAs, the degree of intergenerational income mobility increases by 4.9 percent for workers of generation 2000 and by 4.2 percent for workers of generation 2010. This improvement in the counterfactual economy can be understood in the following way. First, workers from locations with relatively higher employment share in manufacturing can regain upward mobility due to the less structural transformation in the economy, higher TFP relative and more mobility to the productive locations compared to the baseline economy. Second, workers from locations with relatively higher employment share in services gain intergenerational income mobility since they have more mobility between sectors and can sort into places with high productivity in manufacturing. As a result, the general equilibrium effect in the local labor market leads to an increase in relative wages in service industries for locations where employment share in service is large in the baseline economy. Then, workers from service intensive cities can also end up with higher income positions in the economy. Quantitatively, the latter effects are significantly large for selected service intensive cities and we find a larger standard deviation in the degree of intergenerational income mobility across cities in the counterfactual.

In a nutshell, when we remove persistence in job choices over generations, the reallocation of workers between industries and locations leads to the sorting of workers to productive locations and industries in both the manufacturing and service sector and this regains intergenerational income mobility of workers. In terms of an implication of policy, this result is suggestive of the possibility of education in the local economy that can break the persistence in job choices over generations for overcoming the limited upward mobility.

8 Conclusion

The interplay between structural transformation in the aggregate and local economies is key to understanding spatial inequality and worker mobility. To look at this, we have developed a dynamic economic geography model with overlapping generations that accommodates the frictional adjustment of workers across locations and industries, non-homothetic preference and productivity spillovers in a tractable way. The theoretical framework provides insights into the cross-sectional disparity and intergenerational income inequality among workers that arise due to structural changes in the economy. The model is calibrated with the U.S. economy and despite the high number of dimensions – on location, industry and time – the model structure allows us to back out productivity and amenities from the data. And this, in turn, enables us to quantitatively assess the importance of different mechanisms that drive spatial variation in total factor productivity (TFP), welfare dynamics, inequality and intergenerational income mobility. The dynamic nature of the spatial model therefore allows us to study phenomena that have received limited scrutiny but which are of fundamental interest in a country which is increasingly riven by growing inequality and barriers to upward mobility.

This paper allows us to understand how the structure of the spatial economy - through trade and migration, local labor market exposures and agglomeration - shapes individual outcomes. We begin to understand why in the same country, the citizens of San Jose are on entirely different trajectories than those in Cleveland. Why rising levels of inequality might constrain upward mobility as characterized by the Gatsby Curve. Understanding this is critical to understanding how the U.S. as a whole and not just a few cities within it can regain the "land of opportunity" mantle. In effect, this paper is trying to open the black box of how the structure of economy not just across space but also across time can influence patterns of inequality and mobility in different locations. To do this, we perform counterfactual experiments using the parameterized model, which enables us to quantify the importance of technological progress and spatial variation in amenities in determining the pace of structural transformation across locations. Through such counterfactual analysis, we find that the productivity growth of industries that drive structural change and the persistent variation in amenities across geographies is critical to explaining the regional disparity in TFP changes and workers' mobility. We also show that non-homothetic preference and persistence in occupational structure through the different degrees of exposure to industries in the local economy are critical to understanding how mobility can be encouraged and inequality in an economy that is increasingly dominated by services.

The framework proposed is easily extended to quantify the effects of various shocks on local economies and workers within them in the long run. Amongst possible shocks, the interaction between locations and the rapidly changing international market is perhaps the most important to look at. Globalization and in particular the U.S. relationship with China is very much in the spotlight in terms of understanding why some cities in the U.S. have prospered whilst others have declined. Another research avenue we are to pursue is applying my framework to locations within developing countries where the overall pace of structural change tends to be more rapid but where we understand little about distributional effects across space and time. The framework developed in this paper when combined with developing country data serves as an interesting laboratory for understanding variation in inequality and mobility. This understanding is fundamental to designing policies to equalize opportunities across locations within countries, something which is very much at the top of the global policy agenda as the world moves gradually out of the pandemic.

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Appendix to "The Geography of Structural Transformation: Effects on Inequality and Mobility"

A Model

We provide microfoundation and derivation of the choice of industry job. There are a measure of L^j_{it} workers in sector j in location i at period t. The total population of cohort $t+1$ (i.e., next generation) with origin i is $\bar{L}_{it+1} = \sum_{j\in\mathcal{K}} L^j_{it}$. The discussion is not altered when introducing the uniform birth rate across locations. The young generation is ex ante homogeneous and an individual has a unit of time for job choice during the young period. Since the young generation does not obtain utility from consumption or leisure, there is no incentive to spend any time other than on a job choice.

Consider young individuals in location i in period t. During the young period, an individual acquires information from existing workers in location i. Suppose one unit of time is divided into T spans and let $\Delta = 1/T$. In each span Δ, an individual spends the time to acquire information regarding a job in each sector. During time span Δ, an individual receives the valuable (positive) information about sector j with probability g^j_i, and the valueless (negative) information with probability $1-g^j_i$. To achieve the probability g^j_i, an individual must spend time:

$$\mathcal{O}(g^j_i, L^j_{it}) = \Lambda_j \ln\left(\frac{1}{1-g^j_i}\right)(L^j_{it})^{-\eta} \tag{A.1}$$

where Λ_j and η are strictly positive constant.

Then, an individual decides time allocation across different sectors to maximize the logit of probabilities. The large value of logit corresponds to a large value of odds, and maximizing logit implies maximizing the odds of acquiring positive information over acquiring negative information. Alternatively, people minimize the coefficient of variation for the number of valuable information they receive during the period since the coefficient of variation captures the relative variation of successful information acquisition over the average success rate given by $\sqrt{\frac{1-g^j_i}{g^j_i}}$.

In summary, an individual solves:

$$g^j_{it} = \arg\max_{\{g^k_i\}\in(0,1)} \left\{\sum_k \ln\frac{g^k_i}{1-g^k_i} \quad \text{s.t.} \quad \sum_k \mathcal{O}(g^k_i, L^k_{it}) \le \Delta\right\} \tag{A.2}$$

Solution for this is:

$$g^j_{it} = \frac{(L^j_{it})^\eta}{\Lambda_j O_i} \tag{A.3}$$

where O_i is Lagrangian multiplier for individuals that solves:

$$\sum_{k\in\mathcal{K}} \Lambda_k \ln\left(\frac{\Lambda_k O_i}{\Lambda_k O_i - (L^k_{it})^\eta}\right)(L^k_{it})^{-\eta} = \Delta \tag{A.4}$$

Then, the probability that an individual of cohort $t+1$ successfully acquires valuable information during each time Δ is g^j_{it}. The probability of realization of T' successful information acquisition becomes ${}_T\mathrm{C}_{T'}\left(g^j_{it}\right)^{T'}\left(1-g^j_{it}\right)^{T-T'}$ for $T' \le T$. Taking its limit $\Delta \to 0$, for one unit of time, the realization of the number of valuable information follows:

$$\mathcal{B}_{it}^{j}(m) = \frac{(g_{it}^{j})^{m}}{m!}\exp\left(-g_{it}^{j}\right) \tag{A.5}$$

The number of shocks that arrive to individuals of cohort $t+1$ exhibits the average g_{it}^{j} and variance g_{it}^{j}. Intuitively, when $\eta > 0$, the average number is large as existing workers increase as the marginal cost for acquiring positive information is low when L_{it}^{j} is large. Further, many existing workers lead to a large variance in arrivals.

Next, the value of tastes follows Pareto distribution. The value of each shock is supposed to be following Pareto distribution for every sector:

$$F(z) = 1 - (z/\underline{z})^{-\phi}, \quad \phi > 1$$

The important assumption is that the number of arrival shocks is specific to the pair of industry and location, while the size of shocks is independent of industry and location.

An individual picks up the largest value from the tastes. Its cumulative distribution function is:

$$\begin{aligned}\mathcal{F}_{it}^{j}(z) &= \sum_{m=1}^{\infty}\left(\prod_{m'=1}^{m}\mathbf{Pr}\left(z_{it}^{j}(m') \le z\right)\right)\mathcal{B}_{it}^{j}(m) + \mathcal{B}_{it}^{j}(0) \\ &= \sum_{m=0}^{\infty}\left(1-(z/\underline{z})^{-\phi}\right)^{m}\frac{(g_{it}^{j})^{m}e^{-g_{it}^{j}}}{m!} \\ &= e^{-g_{it}^{j}(z/\underline{z})^{-\phi}}\end{aligned} \tag{A.6}$$

Define:

$$G_{it}^{j}(u) = \mathbf{Pr}\left(\bar{U}_{it}^{j}z_{it}^{j} \le u\right) = e^{-\mathcal{V}_{it}^{j}u^{-\phi}} \quad \text{with} \quad \mathcal{V}_{it}^{j} = g_{it}^{j}(\underline{z}\bar{U}_{it+1}^{j})^{\phi} \tag{A.7}$$

The pattern of choosing industry j among cohort $t+1$ in location i becomes:

$$\begin{aligned}\mathbf{Pr}(\bar{U}_{it}^{j}z_{it}^{j} \ge \bar{U}_{it}^{k}z_{it}^{k},\ \forall k \ne j) &= \int_{\underline{u}}^{\infty} g_{it}^{j}(u)\prod_{k\ne j}G_{it}^{k}(u)\mathrm{d}u \\ &= \frac{\mathcal{V}_{it}^{j}}{\sum_{k\in\mathcal{K}}\mathcal{V}_{it}^{k}}\left[e^{-\sum_{k\in\mathcal{K}}\mathcal{V}_{it}^{k}u^{-\phi}}\right]_{\underline{u}}^{\infty} \to \frac{g_{it}^{j}(\bar{U}_{it+1}^{j})^{\phi}}{\sum_{k\in\mathcal{K}}g_{it}^{k}(\bar{U}_{it+1}^{k})^{\phi}} \quad (as\ \underline{z}\to 0)\end{aligned} \tag{A.8}$$

The last equation takes the minimum of Pareto distribution (i.e., lower bound of the Pareto distribution) to zero and expands its support to $(0, \infty)$. The distribution of indirect utility satisfies:

$$1 - G_{it}(u) = 1 - \prod_{j} e^{-\mathcal{V}_{it}^{j}u^{-\phi}} = 1 - e^{-\mathcal{V}_{it}u^{-\phi}}, \quad \mathcal{V}_{it} = \sum_{j}\mathcal{V}_{it}^{j} \tag{A.9}$$

and the average welfare for the generation t born in i is:

$$\int_{\underline{u}}^{\infty} u\mathrm{d}G_{it}(u) = \int_{0}^{\mathcal{V}_{it}\underline{u}^{-\phi}}(y/\mathcal{V}_{it})^{-1/\phi}e^{-y}\mathrm{d}y \to \mathcal{V}_{it}^{1/\phi} \tag{A.10}$$

The average welfare among individuals of generation t who has an origin in location i is equalized ex ante because of the free mobility between sectors (i.e., self-selection) *ex ante*. Yet, there are idiosyncratic shocks in both location choice (i.e., idiosyncratic shocks in amenity) and idiosyncratic shocks in self-selection, so *ex post* utility of individuals is not equalized.

B Equilibrium

This section solves the equilibrium in period $t+1$ given information of the time-varying fundamentals for both periods t and $t+1$ and time-invariant fundamentals and conditional on the equilibrium in period t. To economize notation, use the following notations for exogenous factors:

$$\mathbb{A}^j_{int} = (A^j_{it}/\tau^j_{int})^{\theta_j}, \quad \mathbb{B}^j_{int} = (B^j_{it}/D_{int})^{\varepsilon}$$

The income of workers is:

$$W^j_{it+1} = \varsigma_{it+1} w^j_{it+1} = \left(1 + \frac{1-\chi}{\chi} \frac{w^0_{it+1} L^0_{it+1}}{\sum_k w^k_{it+1} L^k_{it+1}}\right) w^j_{it+1} \tag{B.1}$$

Therefore, income of individuals (W^j_{it+1}) is uniquely determined by wages ($\boldsymbol{w}$) and employment distribution ($\boldsymbol{L}$). The expected utility conditional on sector choice ($\bar{U}^j_{it+1}$), welfare measure (V_{it+1}) and real income ($\mathcal{W}^j_{it+1}$) satisfy:

$$\begin{aligned} (\bar{U}^j_{it+1})^{\varepsilon} &= \sum_{\ell} \mathbb{B}^j_{\ell it+1} (\mathcal{W}^j_{\ell t+1})^{\varepsilon} \\ (V_{it+1})^{\phi} &= \sum_j \zeta_j (L^j_{it})^{\eta} (\bar{U}^j_{it+1})^{\phi} \end{aligned} \tag{B.2}$$

Then, we can define unique mapping between expected utility ($\bar{U}^j_{it+1}$), welfare measure (V_{it+1}) and real income ($\mathcal{W}^j_{it+1}$). In particular, expected utility determines welfare measure and real income uniquely by (B.2). We can define unique mapping between real income ($\mathcal{W}^j_{t+1}$) to average utility ($\bar{U}^j_{t+1}$) and the mapping is increasing and homogeneous of degree one.

Labor mobility leads to employment in location i and sector j in period $t+1$:

$$L^j_{it+1} = \sum_n \left(\frac{\mathbb{B}^j_{int+1} (\mathcal{W}^j_{it+1})^{\varepsilon}}{\sum_{\ell} \mathbb{B}^j_{\ell nt+1} (\mathcal{W}^j_{\ell t+1})^{\varepsilon}} \left(\frac{\zeta_j (L^j_{nt})^{\eta} \left(\sum_{\ell} \mathbb{B}^j_{\ell nt+1} (\mathcal{W}^j_{\ell t+1})^{\varepsilon}\right)^{\phi/\varepsilon}}{\sum_k \zeta_k (L^k_{nt})^{\eta} \left(\sum_{\ell} \mathbb{B}^k_{\ell nt+1} (\mathcal{W}^k_{\ell t+1})^{\varepsilon}\right)^{\phi/\varepsilon}} \right) L_{nt} \right) = S^j_{it+1}(\boldsymbol{\mathcal{W}}) \tag{B.3}$$

Employment is uniquely determined by the real income and the mapping is increasing and homogeneous of degree zero in real income, $S^j_{it+1}(\boldsymbol{\mathcal{W}})$. When $\varepsilon < \phi$, we have the followings:

$$\frac{dS^j_{it+1}(\boldsymbol{\mathcal{W}})}{d\mathcal{W}^j_{it+1}} > \frac{dS^j_{it+1}(\boldsymbol{\mathcal{W}})}{d\mathcal{W}^j_{nt+1}} > 0, \quad \frac{dS^j_{it+1}(\boldsymbol{\mathcal{W}})}{d\mathcal{W}^k_{nt+1}} < 0 \tag{B.4}$$

for $n \neq i$ and $k \neq j$. Productivity spillover implies:

$$Z^j_{it+1} = A^j_{it+1} \mathbb{Z}^j_{it+1}(\boldsymbol{\mathcal{W}}) (L^j_{it+1})^{\gamma_j}, \tag{B.5}$$

where $\mathbb{Z}^j_{it+1}(\boldsymbol{\mathcal{W}})$ is endogenous component of productivity through labor mobility. Given previous labor allocation (L^j_{it}) and previous productivity (Z^j_{it}), real income in period $t+1$ determines the endogenous part of productivity uniquely. $\mathbb{Z}^j_{it+1}(\cdot)$ is homogeneous of degree zero.

And tradable goods price in location n and sector j becomes

$$(p^j_{nt+1})^{-\theta_j} = \Gamma_j^{-\theta_j} \left(\sum_i \mathbb{A}^j_{nit+1} \left(\mathbb{Z}^j_{it+1}(\boldsymbol{\mathcal{W}}) (L^j_{it+1})^{\gamma_j} (w^j_{it+1})^{-\beta_j} \left(\prod_{j' \in \mathcal{K} \setminus 0} (p^{j'}_{it+1})^{-\beta_{jj'}} \right) \right)^{\theta_j} \right) \tag{B.6}$$

Since $\left| \frac{\mathrm{d} \ln p^j_{it+1}}{\mathrm{d} \ln p^{j'}_{nt+1}} \right| = \beta_{jj'} \pi^j_{int+1} < 1$ for any combination of (i,j) and (n,j'), (B.6) is solved for unique prices (p^j_{it+1}) given wages ($\boldsymbol{w}$), real income ($\boldsymbol{\mathcal{W}}$) and employment ($\boldsymbol{L}$). To simplify the discussion in the following, we set $\beta_{jj'} = 0$. Therefore, (B.6) is reduced to

$$(p^j_{nt+1})^{-\theta_j} = \Gamma_j^{-\theta_j} \left(\sum_i \mathbb{A}^j_{nit+1} \left(\frac{w^j_{it+1}}{\mathbb{Z}^j_{it+1}(\boldsymbol{\mathcal{W}})} \right)^{-\theta_j} (L^j_{it+1})^{\tilde{\gamma}_j} \right) \tag{B.7}$$

where $\tilde{\gamma}_j = \gamma_j \theta_j$. Price index satisfies:

$$\left(P^j_{it+1}\right)^{1-\sigma} = \sum_k \alpha_k^{\sigma-1} (p^k_{it+1})^{1-\sigma} (W^j_{it+1}/P^j_{it+1})^{\mu_k - 1}, \tag{B.8}$$

and this can be expressed by using real income:

$$(\mathcal{W}^j_{it+1})^{1-\sigma} = \frac{(W^j_{it+1})^{1-\sigma}}{\sum_k \left(\left(\frac{\Gamma_k}{\alpha_k}\right)^{1-\sigma} \left(\sum_n \mathbb{A}^k_{int+1} \left(\frac{w^k_{nt+1}}{\mathbb{Z}^k_{nt+1}(\boldsymbol{\mathcal{W}})} \right)^{-\theta_k} (L^k_{nt+1})^{\tilde{\gamma}_k} \right)^{-(1-\sigma)/\theta_k} (\mathcal{W}^j_{it+1})^{\mu_k - 1} \right) + \left(\frac{p^0_{it+1}}{\alpha_0} \right)^{1-\sigma} (\mathcal{W}^j_{it+1})^{\mu_0 - 1}} \tag{B.9}$$

Expenditure share to good j by individuals in n and sector k becomes:

$$\psi^k_{j|nt+1} = \frac{\alpha_j^{\sigma-1} (p^j_{nt+1})^{1-\sigma} (\mathcal{W}^k_{nt+1})^{\mu_j - 1}}{\sum_s \alpha_s^{\sigma-1} (p^s_{nt+1})^{1-\sigma} (\mathcal{W}^s_{nt+1})^{\mu_j - 1}} \tag{B.10}$$

Labor market clearing condition is:

$$L^j_{it+1} = \frac{1}{w^j_{it+1}} \sum_n \pi^j_{int+1} Y^j_{nt+1}, \tag{B.11}$$

where Y^j_{nt+1} refer total expenditure of workers to good j in n. Therefore, in equilibrium, labor market clearing condition can be rewritten by:

$$w^j_{it+1} = \frac{1}{L^j_{it+1}} \sum_n \left(\frac{\mathbb{A}^j_{nit+1} (w^j_{it+1}/\mathbb{Z}^j_{it+1}(\boldsymbol{\mathcal{W}}))^{-\theta_j} (L^j_{it+1})^{\tilde{\gamma}_j}}{\sum_\ell \mathbb{A}^j_{n\ell t+1} (w^j_{\ell t+1}/\mathbb{Z}^j_{\ell t+1}(\boldsymbol{\mathcal{W}}))^{-\theta_j} (L^j_{\ell t+1})^{\tilde{\gamma}_j}} \right.$$
$$\left. \sum_k \left(\frac{\alpha_j^{\sigma-1} \left(\Gamma_j^{1-\sigma} \left(\sum_i \mathbb{A}^j_{nit+1} \left(\frac{w^j_{it+1}}{\mathbb{Z}^j_{it+1}(\boldsymbol{\mathcal{W}})} \right)^{-\theta_j} (L^j_{it+1})^{\tilde{\gamma}_j} \right) \right)^{-(1-\sigma)/\theta_j} (\mathcal{W}^k_{nt+1})^{\mu_j - 1}}{\sum_s \alpha_s^{\sigma-1} \left(\Gamma_s^{1-\sigma} \left(\sum_i \mathbb{A}^s_{nit+1} \left(\frac{w^s_{it+1}}{\mathbb{Z}^s_{it+1}(\boldsymbol{\mathcal{W}})} \right)^{-\theta_s} (L^s_{it+1})^{\tilde{\gamma}_s} \right) \right)^{-(1-\sigma)/\theta_s} (\mathcal{W}^s_{nt+1})^{\mu_j - 1}} W^k_{nt+1} L^k_{nt+1} \right) \right) \tag{B.12}$$

For sector 0, labor market clearing condition is:

$$w^0_{it+1} = \chi p^0_{it} \bar{H}_{it} (L^0_{it})^{\chi - 1} \tag{B.13}$$

where $\bar{H}_{it} = \nu_i ((1 - \bar{h}_i) H_{it})^{1-\chi}$ is predetermined variables of stocks in period $t+1$. Lastly, for sector 0, manipulating market clearing condition yields:

$$p^0_{it+1} = \left(\frac{\alpha_0}{(1-\chi)\bar{H}_{it}} \sum_j \frac{(\mathcal{W}^j_{it+1})^{\mu_0 - \sigma} (W^j_{it+1})^{\sigma}}{L^0_{it+1}} L^j_{it+1} \right)^{1/\sigma} \tag{B.14}$$

The equilibrium in period $t+1$ is fully characterized by wages ($\boldsymbol{w}$), employment allocation ($\boldsymbol{L}$), real income ($\boldsymbol{\mathcal{W}}$) and price of non-tradable sector ($\boldsymbol{p}$) that solve equations: (i) labor mobility (B.3); (ii) utility maximization (B.9); (iii) labor market clearing condition (B.12) and (B.13); and (iv) structure market clearing condition (B.14), together. The analytical augment for solving the system is followings. We plug (B.14) into (B.9) and (B.13) and focus on ($\boldsymbol{w}$), employment allocation ($\boldsymbol{L}$) and real income ($\boldsymbol{\mathcal{W}}$). Then, the system of equations (B.3), (B.9), (B.12) and (B.13) consists of $3 \times N \times (K+1)$ equations for the same number of endogenous variables. By construction, the system of equations takes a form of fixed point equations. Specifically, the right-hand sides of equations (B.3), (B.9), (B.12) and (B.13) define continuous mapping from the region $\mathbb{R}^{3\times N \times (K+1)}$ to itself. We suppose that exogenous location and sectoral characteristics are positive and finite.

Then, for positive and finite wages and employment, $w^j_{it+1} \in (0,\infty)$ and $L^j_{it+1} \in (0,\infty)$, we can constitute convex subset of $\mathbb{R}^{N\times(K+1)}_{++}$ for real income and (B.9) provides existence of such positive and finite real income, $\mathcal{W}^j_{it+1} \in (0,\infty)$. By using the same augment, we can define the convex subset in $\mathbb{R}^{3\times N\times(K+1)}_{++}$ for wages, employment and real income such that we can characterize the positive and finite equilibrium variables, $w^j_{it+1} \in (0,\infty)$, $L^j_{it+1} \in (0,\infty)$ and $\mathcal{W}^j_{it+1} \in (0,\infty)$.

In order to discuss the uniqueness of equilibrium analytically, consider the conservative case: $\rho = 0$ and $\chi = 1$. $\rho = 0$ implies that productivity spillover happened locally, and $\chi = 1$ implies that supply of structure is elastic. This simplifies:

$$W^j_{it+1} = w^j_{it+1}, \quad Z^j_{it+1} = (L^j_{it+1})^{\gamma_j}, \quad p^0_{it+1} = w^0_{it+1} \tag{B.15}$$

Equation (B.9) becomes:

$$\mathcal{W}^j_{it+1} = \frac{w^j_{it+1}}{\left(\sum_k \left(\left(\frac{\Gamma_k}{\alpha_k}\right)^{1-\sigma}\left(\sum_n \mathbb{A}^k_{int+1}\left(w^k_{nt+1}\right)^{-\theta_k}(L^k_{nt+1})^{\tilde{\gamma}_k}\right)^{-(1-\sigma)/\theta_k}(\mathcal{W}^j_{it+1})^{\mu_k-1}\right) + \left(\frac{w^0_{it+1}}{\alpha_0}\right)^{1-\sigma}(\mathcal{W}^j_{it+1})^{\mu_0-1}\right)^{1/(1-\sigma)}} \tag{B.16}$$

By solving this for real income ($\boldsymbol{\mathcal{W}}$), we obtain unique mapping from wages ($\boldsymbol{w}$) and employment ($\boldsymbol{L}$) to real income. Further, (B.12) becomes:

$$\begin{aligned}\Gamma_j^{-(1-\sigma)} L^j_{it+1} = \frac{\alpha_j^{\sigma-1}}{w^j_{it+1}} \sum_n \Bigg(& \frac{\mathbb{A}^j_{nit+1}(w^j_{it+1})^{-\theta_j}(L^j_{it+1})^{\tilde{\gamma}_j}}{\sum_{\ell'} \mathbb{A}^j_{n\ell't+1}(w^j_{\ell't+1})^{-\theta_j}(L^j_{\ell't+1})^{\tilde{\gamma}_j}} \\ & \times \left(\sum_\ell \mathbb{A}^j_{n\ell t+1}(w^j_{\ell t+1})^{-\theta_j}(L^j_{\ell t+1})^{\tilde{\gamma}_j}\right)^{-(1-\sigma)/\theta_j}\left(\sum_k (w^k_{nt+1})^{\sigma}(\mathcal{W}^k_{nt+1})^{\mu_j-\sigma}L^k_{nt+1}\right)\Bigg)\end{aligned} \tag{B.17}$$

Manipulating this yields

$$\begin{aligned}\Gamma_s^{-(1-\sigma)}(L^j_{it+1})^{1-\tilde{\gamma}_j} = \frac{\alpha_j^{\sigma-1}}{(w^j_{it+1})^{1+\theta_j}} \sum_n \Bigg(& \mathbb{A}^j_{nit+1}\left(\sum_\ell \mathbb{A}^j_{n\ell t+1}(w^j_{\ell t+1})^{-\theta_j}(L^j_{\ell t+1})^{\tilde{\gamma}_j}\right)^{-1-(1-\sigma)/\theta_j} \\ & \times \left(\sum_k (w^k_{nt+1})^{\sigma}\left(\frac{L^k_{nt+1}}{\sum_\ell \mathbb{B}^k_{n\ell t+1}\kappa^k_{\ell t+1}(\bar{U}^k_{\ell t+1})^{-\varepsilon}L_{\ell t}}\right)^{(\mu_j-\sigma)/\varepsilon} L^k_{nt+1}\right)\Bigg)\end{aligned} \tag{B.18}$$

Letting $J^j_i(\boldsymbol{L})$ refer the right-hand side of (B.18), the gross substitute property holds for $J^j_i(\boldsymbol{L})$ when $\tilde{\gamma}_j < 1$. When the gross substitute holds and $0 < \tilde{\gamma}_j < 1$, unique solution exists for (B.18) when homogeneity of $J^j_i(\boldsymbol{L})$ satisfies:

$$\tilde{\gamma}_j\left(1 + \frac{1-\sigma}{\theta_j}\right) - \frac{\mu_j - \sigma}{\varepsilon} + (\mu_j - \sigma) - 1 < -1 \tag{B.19}$$

This condition is intuitive. When $\varepsilon \to \infty$, idiosyncratic shocks in migration is homogeneous and it leads to lower threshold for γ_j as weak agglomeration forces are required to avoid generating multiple equilibria. If μ_j becomes large, this condition becomes slack. This implies that large heterogeneity in consumption across workers of different income leads to more dispersion of workers to avoid multiple equilibria. Further discussion can be found later for quantification.

Labor demand schedule solving (B.18) downward slope of wage. For labor supply, (B.3) argues that the labor supply schedule is upward slope of wage, therefore pinning down wage vector that clear the labor market.

C Spatial Dynamics of the Economy

This section presents TFP measure and its change (Subsection C.1), welfare (Subsection C.2) and measure of the upward mobility of workers (Subsection C.3).

C.1 Local Measured TFP

The measured total factor productivity (TFP) in location i and sector j at time t is given by:

$$\ln \delta_{it}^{j} = -\frac{1}{\theta_j} \ln \pi_{iit}^{j} + \ln Z_{it}^{j} \tag{C.1}$$

and the overall productivity is

$$\ln Z_{it}^{j} = \ln A_{it}^{j} + \rho \ln \sum_{n} L_{int}^{j} Z_{nt-1}^{j} + \gamma_j \ln L_{it}^{j} \tag{C.2}$$

Letting

$$\widetilde{z}_{in,t}^{s} = \frac{L_{in,t}^{s} Z_{n,t-1}^{s}}{\sum_{\ell} L_{i\ell,t}^{s} Z_{\ell,t-1}^{s}}, \quad \widetilde{l}_{in,t}^{s} = \frac{L_{in,t}^{s}}{\sum_{\ell} L_{i\ell,t}^{s}},$$

the change of local TFP is

$$\frac{d \ln \delta_{it}^{j}}{d \ln A_{it}^{j}} = 1 - \frac{1}{\theta_j} \frac{d \ln \pi_{iit}^{j}}{d \ln A_{it}^{j}} + \sum_{n} \left(\rho \widetilde{z}_{int}^{j} + \gamma_j \widetilde{l}_{int}^{j} \right) \left(\frac{d \ln \lambda_{int}^{j}}{d \ln A_{it}^{j}} + \frac{d \ln \kappa_{nt}^{j}}{d \ln A_{it}^{j}} \right) \tag{C.3}$$

(C.3) gives the spatial variation of TFP growth along with the technological shock. The second term translates the comparative advantage in trade and its gain is different across locations. The third term captures the migration effects and persistency of workers' choice of industry. These effects change the TFP gains or losses through economies of scale and spillover through workers' mobility. Further, (C.2) can be expressed by

$$\ln \delta_{it}^{j} + \frac{1}{\theta_j} \ln \pi_{iit}^{j} = \ln A_{it}^{j} + \rho \ln \sum_{n} L_{int}^{j} \left((\pi_{nnt-1}^{j})^{1/\theta_j} \delta_{nt-1}^{j} \right) + \gamma_j \ln L_{it}^{j} \tag{C.4}$$

In the steady state,

$$\ln \delta_{i}^{j} + \frac{1}{\theta_j} \ln \pi_{ii}^{j} = \ln A_{i}^{j} + (\gamma_j + \rho) \ln L_{i}^{j} + \rho \Delta_{i}^{j} + \rho \sum_{n} \frac{L_{in}^{j}}{L_{i}^{j}} \left(\ln \delta_{n}^{j} + \frac{1}{\theta_j} \ln \pi_{nn}^{j} \right) \tag{C.5}$$

where $\Delta_{i}^{j} > 0$ is appropriate positive value. Letting

$$\vec{\boldsymbol{\delta}}_j = \{ \ln \delta_{i}^{j} + \frac{1}{\theta_j} \ln \pi_{ii}^{j} \}, \quad \vec{\boldsymbol{A}}_j = \{ \ln A_{i}^{j} + (\gamma_j + \rho) \ln L_{i}^{j} + \rho \Delta_{i}^{j} \}, \quad \mathbf{L}_j = \{ \widetilde{l}_{in}^{j} \},$$

denote $N \times 1$ vectors and $N \times N$ matrix respectively, the equation leads to:

$$\vec{\boldsymbol{\delta}}_j = \left(\mathbf{I} - \rho \mathbf{L}_j \right)^{-1} \vec{\boldsymbol{A}}_j$$

If the spectral radius of $\rho \mathbf{L}_j$ is less than 1, the local TFP in the steady state is given by:

$$\ln \delta_{i}^{j} = -\frac{1}{\theta_j} \ln \pi_{ii}^{j} + \sum_{n} \left\{ \sum_{m=0}^{\infty} (\rho \mathbf{L}_j)^m \right\}_{in} (\ln A_{n}^{j} + (\gamma_j + \rho) \ln L_{n}^{j} + \rho \Delta_{n}^{j}) \tag{C.6}$$

where $\{\sum_{m=0}^{\infty} (\rho \mathbf{L}_j)^m\}_{in}$ is $i - n$ th element of the matrix. The level of local TFP is decomposed into import penetration and spillover in productivity through labor mobility. The latter effect is governed by the matrix:

$$\mathbf{K} = \sum_{m=0}^{\infty} (\rho \mathbf{L}_j)^m = \sum_{m=0}^{\infty} \rho^m \{ \lambda_{in}^{j} \kappa_{n}^{j} L_{n}^{j} \}^m$$

This is given in Proposition 2 in the main text.

C.2 Welfare Implications

Location choice probability satisfies:

$$\lambda_{iit}^{j} = \left(\frac{B_{it}^{j}\mathcal{W}_{it}^{j}}{D_{iit}\bar{U}_{it}^{j}}\right)^{\varepsilon} = \left(\frac{B_{it}^{j}\zeta_{j}^{1/\phi}\mathcal{W}_{it}^{j}\left(L_{it-1}^{j}\right)^{\eta/\phi}}{D_{iit}V_{it}\left(\kappa_{it}^{j}\right)^{1/\phi}}\right)^{\varepsilon}$$

Using the expenditure share on tradable goods, this becomes:

$$\lambda_{iit}^{j} = \left(\frac{\zeta_{j}^{1/\phi}B_{it}^{j}\left(\alpha_{j}W_{it}^{j}\right)^{(1-\sigma)/(\mu_{j}-\sigma)}\left(L_{it-1}^{j}\right)^{\eta/\phi}\left(\psi_{j|it}^{j}\right)^{1/(\mu_{j}-\sigma)}}{\left(p_{it}^{j}\right)^{(1-\sigma)/(\mu_{j}-\sigma)}V_{it}\left(\kappa_{it}^{j}\right)^{1/\phi}}\right)^{\varepsilon} \tag{C.7}$$

In the followings, B_{it}^{j} is constant to focus on the endogenous mechanisms. Price of tradable final goods satisfy

$$\ln p_{it}^{j} = \ln\left(\Gamma_{j}(w_{it}^{j})^{\beta_{j}}(\pi_{iit}^{j})^{1/\theta_{j}}\frac{1}{Z_{it}^{j}}\right) + \sum_{s}\beta_{js}\ln p_{it}^{s} \tag{C.8}$$

Letting

$$\widetilde{\boldsymbol{p}}_{it} = \left\{\ln p_{it}^{j}\right\}, \quad \widetilde{\mathbf{B}} = \left\{\beta_{jk}\right\}, \quad \boldsymbol{C}_{it} = \left\{\ln\Gamma_{j}(w_{it}^{j})^{\beta_{j}}(\pi_{iit}^{j})^{1/\theta_{j}}\frac{1}{Z_{it}^{j}}\right\}$$

be corresponding vector and matrix. Then, price of final goods is:

$$\widetilde{\boldsymbol{p}}_{it} = \left(\mathbf{I} - \widetilde{\mathbf{B}}\right)^{-1}\boldsymbol{C}_{it}$$

Letting $\tilde{\beta}_{kj}$ be elements of matrix $\left(\mathbf{I} - \widetilde{\mathbf{B}}\right)^{-1}$, price of tradable goods are:

$$p_{it}^{j} = \prod_{s}\left(\frac{\Gamma_{s}(w_{it}^{s})^{\beta_{s}}}{Z_{it}^{s}}(\pi_{iit}^{s})^{1/\theta_{s}}\right)^{\widetilde{\beta}_{js}} \tag{C.9}$$

Plugging this into above and manipulating it, we derive:

$$V_{it} = \bar{\gamma}_{j}(\lambda_{iit}^{j})^{-1/\varepsilon}\left(\prod_{s}(\pi_{iit}^{s})^{-\widetilde{\beta}_{js}/\theta_{s}}\right)^{\widetilde{\mu}_{j}}\left(\prod_{s}\left(\frac{(w_{it}^{s})^{\beta_{s}}}{Z_{it}^{s}}\right)^{-\widetilde{\beta}_{js}}\right)^{\widetilde{\mu}_{j}} W_{it}^{j\,\widetilde{\theta}_{j}}\psi_{j|it}^{j\;\;\widetilde{\mu}_{j}/(1-\sigma)}\kappa_{it}^{j\;-1/\phi}L_{it-1}^{j\;\;\;\eta/\phi}$$

where $\widetilde{\mu}_{j} = (1-\sigma)/(\mu_{j}-\sigma)$ and $\bar{\gamma}_{j}$ is constant. Therefore, welfare of generation t born in i relative to that of generation $t-1$ born in i is:

$$\begin{aligned} d\ln V_{it} \propto \sum_{s\in\mathcal{K}\setminus 0}\Bigg(&\widetilde{\mu}_{s}\beta_{s}\sum_{j}\widetilde{\beta}_{sj}\left(d\ln\delta_{it}^{j} - d\ln w_{it}^{j}\right) - \widetilde{\mu}_{s}\left((1-\beta_{s})\sum_{j}\widetilde{\beta}_{sj}\frac{d\ln\pi_{iit}^{j}}{\theta_{j}}\right) \\ &-\frac{d\ln\lambda_{iit}^{s}}{\varepsilon} + \widetilde{\mu}_{s}\frac{d\ln e_{s|it}^{s}}{1-\sigma} - \frac{d\ln\kappa_{it}^{s}}{\phi} + \frac{\eta}{\phi}d\ln L_{it-1}^{s}\Bigg) \end{aligned} \tag{C.10}$$

where $e_{s|i,t}^{s} = \psi_{s|it}^{s}w_{it}^{s}$. This is given in Proposition 3 in text.

C.3 Intergenerational Mobility

Notation. $W_{it}^{\mathbf{o}}(\omega)$ is income of individual worker ω of generation t working in location i. $W_{it+1}^{\mathbf{y}}(\omega)$ is income of individual of generation $t+1$ (i.e., children) who has origin in location i. In the model, income distribution in the economy is the probability mass function, as the model derives the discrete finite number of possible income levels in the economy. Let $\mathbb{Y}_{t}$ denote the set of income levels in the economy and $\mathbb{Y}_{it}$ denote that in location i. $\mathcal{Q}_{t}(\cdot)$ is the probability distribution function for the income in period t in the whole economy in our model, and $\mathcal{Q}_{t+1}(\cdot)$ is that for period $t+1$. They are model based distributions, while we refer to $\mathcal{Q}_{t}^{*}(\cdot)$ and $\mathcal{Q}_{t+1}^{*}(\cdot)$ as those in data, so they are continuous distribution. $\bar{\varphi}_{it}(y)$ denotes the probability mass function for income y in location i at period t and $\varphi_{t+1}(y|i \to n)$ denotes the probability mass function of income level y among people of generation $t+1$ who move from location i to n. They satisfy: $\sum_{y \in \mathbb{Y}_{it}} \bar{\varphi}_{it}(y) = 1$ and $\sum_{y \in \mathbb{Y}_t} \varphi_{t+1}(y|i \to n) = 1$.

Measure of average upward mobility. Define:

$$\mathcal{R}^{\mathbf{o}}_{nt} = \mathbb{E}[\mathcal{Q}^*_t(W^{\mathbf{o}}_{nt}(\omega))] = \int_0^\infty \bar{\varphi}_{nt}(y)\mathcal{Q}^*_t(y)dy,$$
$$\mathcal{R}^{\mathbf{y}}_{nt+1} = \mathbb{E}[\mathcal{Q}^*_{t+1}(W^{\mathbf{y}}_{nt+1}(\omega))] = \sum_{\ell \in \mathcal{N}} \int_0^\infty \varphi_{t+1}(y|n \to \ell)\mathcal{Q}^*_{t+1}(y)dy$$

Then, a measure for the average upward mobility corresponding is the ratio of these two measures:

$$M_{nt+1} = \mathcal{R}^{\mathbf{y}}_{nt+1}/\mathcal{R}^{\mathbf{o}}_{nt}$$

This measure is related to the equilibrium variables in the model. First,

$$\mathcal{R}^{\mathbf{o}}_{it} = \sum_{s \in \mathcal{K}} f^s_{it} \times \mathcal{Q}_t(\varsigma_{it} w^s_{it})$$

where $\mathcal{Q}_t(\varsigma_{it} w^s_{it})$ is the percentile of workers with income $\varsigma_{it} w^s_{it}$ in the entire economy. Given the probability mass function for the income in each location across sectors, $\bar{\varphi}_{it}(y)$ is corresponding to the share of employment in different sector.

Next, income of generation $t+1$ from location i can yield $N \times (S+1)$ possible incomes in equilibrium. The proportion of each income level is identical to the choice probability of the industry and destination for work. Hence, the corresponding measure is:

$$\mathcal{R}^{\mathbf{y}}_{it+1} = \sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{K}} \lambda^s_{nit+1} \kappa^s_{it+1} \times \mathcal{Q}_{t+1}(\varsigma_{nt+1} w^s_{nt+1}) \tag{C.11}$$

This is the average rank of generation $t+1$ from the origin i. Combining them, the measure (C.3) becomes:

$$M_{it+1} = \sum_{s \in \mathcal{K}} \kappa^s_{it+1} \left(\sum_{n \in \mathcal{N}} \lambda^s_{nit+1} \frac{\mathcal{Q}_{t+1}(\varsigma_{nt+1} w^s_{nt+1})}{\sum_{k \in \mathcal{K}} f^k_{it} \mathcal{Q}_t(\varsigma_{it} w^k_{it})} \right) \tag{C.12}$$

Using the mass probability function, the rank of income is represented by:

$$\mathcal{Q}^k_{it} \equiv \mathcal{Q}_t(\varsigma_{it} w^k_{it}) = \sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{K}} f^s_{nt} \cdot \mathbb{1}_Z(\varsigma_{nt} w^s_{nt} \leq \varsigma_{it} w^k_{it}) \frac{L_{nt}}{\bar{L}}$$

This is the percentile of workers with income $\varsigma_{it} w^k_{it}$ at the national level. Then, the measure (C.12) is rewritten by:

$$M_{it+1} = \sum_{s \in \mathcal{K}} \varsigma^s_{it+1} \frac{\mathcal{Q}^s_{it}}{\sum_{k \in \mathcal{K}} f^k_{it} \mathcal{Q}^k_{it}} \frac{\mathcal{Q}^s_{it+1}}{\mathcal{Q}^s_{it}} \left(\sum_{n \in \mathcal{N}} \lambda^s_{nit+1} \frac{\mathcal{Q}^s_{nt+1}}{\mathcal{Q}^s_{it+1}} \right) \tag{C.13}$$

This is given in the proposition in main text. High value of M_{it+1} implies that the next generation $(t+1)$ are *expected* to be climbing up the income ladder compared to the *average standard* of their parents (generation t). Its heterogeneity across space comes from the difference in each elements at work in (C.13).

To see the asymmetric effect between emigrants and stayers in the location i, consider the decomposition of (C.13) into different types of workers. First, let

$$\mathbb{Q}^s_{it+1} = \frac{\mathcal{Q}^s_{it}}{\sum_{k \in \mathcal{K}} f^k_{it} \mathcal{Q}^k_{it}} \frac{\mathcal{Q}^s_{it+1}}{\mathcal{Q}^s_{it}}. \tag{C.14}$$

This part in (C.13) shows the relative wage growth of the sector in the local economy. Apart from workers' choice of industry and location, the industry growth of *ex-ante* high-wage sector is associated with an increase of upward mobility. Now, we straightforward obtain:

$$M_{it+1} = \sum_{s\in\mathcal{K}} \mathbb{Q}^s_{it+1}\kappa^s_{it+1} + \sum_{s\in\mathcal{K}} \mathbb{Q}^s_{i,t+1}\kappa^s_{it+1} \sum_{n\in\mathcal{N}\setminus i} \lambda^s_{nit+1}\left(\frac{\mathcal{Q}^s_{nt+1}}{\mathcal{Q}^s_{it+1}} - 1\right) \tag{C.15}$$

The first term is the sector specificity in the local labor market and income growth of natives in i (i.e., workers of generation $t+1$ who do not move to other locations). The second term is the location i's land of opportunity for emigrants. When location i has greater labor market access for the growing industries, this allows workers to climb up the income ladder by reallocation.

D Quantification of the Model

Here, we explain the procedure of calibration for the quantitative analysis. We start with the description of data in Subsection D.1. We explain the calibration of the parameters in Subsection D.2. Using the data and parameters, we discuss how to use the model structure to obtain fundamentals in our model in Subsection D.3.

D.1 Data

Cities. We focus on U.S. Core Based Statistical Areas (CBSAs). We use the definition of CBSAs based on Census 2010. Each CBSA consists of a unique county or multiple counties anchored by an urban center of at least 10,000 population and adjacent counties. We use 395 CBSAs in the calibration, where we are able to compute wages and employment throughout time. The 395 CBSAs include all metropolitan areas in the U.S., excluding Alaska and Hawaii and some large micropolitan areas. Since the definition of CBSAs is based on the social and economic linkages between counties and commuting, we take them as our units of cities in the U.S. economy. Throughout time, we fix the definition of CBSAs to exclude the potential problem arising from the change of geographical size that is outside our model.

Industries. We consider the fixed set of industries throughout time. The economy consists of three different groups of industries. We let $\mathcal{K}^{\mathrm{M}}$ refer to the set of manufacturing industries, $\mathcal{K}^{\mathrm{S}}$ refer to the set of service industries, and $\mathcal{K}^{0}$ refer to the single sector related to the immobile structure in the model. We use a crosswalk between industry codes to define each industry for different years based on 4 digit SIC 87. We assign industries to each group as follows. The group of manufacturing sector $\mathcal{K}^{\mathrm{M}}$ consists of: Food, beverage, and tobacco product (4 digit: 2000 to 2141); Textile, textile product mills, apparel, leather, and allied product (4 digit: 2200 to 2399); Wood product, paper, printing, and related support activities (4 digit: 2400 to 2796); Chemical, petroleum, rubber and coal products, and nonmetallic mineral product (4 digit: 2800 to 3299); Metal and fabricated metal product (4 digit: 3300 to 3499); Machinery (4 digit: 3500 to 3599); Computer and electronic product, and Electrical equipment and appliance (4 digit: 3600 to 3699); Transportation equipment (4 digit: 3700 to 3799); Furniture and related product, and Miscellaneous manufacturing (4 digit: 3800 to 3999).

The group of industries $\mathcal{K}^{S}$ consists of: Transport services and storage (4 digit: 4000 to 4789); Wholesale trade (4 digit: 5000 to 5199); Retail (4 digit: 5200 to 5999); Finance, insurance and real estate (4 digit: 6000 to 6799); Health service and social services (4 digit: 8000 to 8099, 8300 to 8399); Legal service and education service (4 digit: 8100 to 8299); Communication service (4 digit: 4800 to 4971); Other local services (4 digit: 7000 to 7999, 8400 to 8811).

The construction sector includes 4 digit: 1500 to 1799. We do not include agriculture, forestry, fishing (4 digit: 0100 to 0971), mining (4 digit: 1000 to 1499) and the rest (4 digit over 9000) in our analysis since these sectors show a small share of employment in the period we analyze.

Wages and employment. Wages and employment are essential to calibrate the model. We construct wages and employment by industry and CBSA. Our data source for employment is the County Business Pattern (CBP) in 1980, 1990, 2000 and 2010. Following procedures to impute employment counts by county and 4-digit SIC 87 industry in David et al. (2013) and using the methodology in Acemoglu et al. (2016), we imputed employment for each county. After the imputation, we aggregate them at the CBSA level to define industry employment.

For wages, we use the American Community Survey (ACS) and decennial censuses. The datasets are downloaded from IPUMS using standardized variables. For the years 1980, 1990 and 2000, we exploit a 5 sample of the respective censuses. For the year 2010, we are based on ACS data. Within each CBSA, we compute the log of average wages across counties for each industry. Wages are inflated to the year 2010 using the Personal Consumption Expenditure Index. Through this process, we can obtain 395 CBSAs that we focus on.

D.2 Parameters

We set parameters in the model. Further details are found in the supplementary material.

Demand. We set the elasticity of substitution $\sigma = 0.4$ as a baseline value. This is consistent with the traditional values in the macroeconomic literature on structural transformation. The parameter μ_j defines the sector-specific Engel slope and α_j is the shift of expenditure. For the service sectors, we set: $(\mu_j - \sigma)/(1 - \sigma) = 1.75$, which is the middle in the range of estimates in Table I in Comin et al. (2021). This implies that $\mu_j = 1.375$ for services. For other industries, we normalize $\mu_j = 1$. This implies that we capture the demand-driven structural transformation at the aggregated level between manufacturing, service, and housing by setting three different parameters. Turning to the scale parameters (α_j), we also consider three different parameters for each aggregation. We set $\alpha_j = 3.0$ for manufacturing. For the other two aggregated sectors, we match the parameter α_j such that the average expenditure share is matched to the aggregate expenditure share. These parameters of the shifter are constant over time.

Technology parameters. The BEA table allows us to specify the identity of input-output in each sector. Then, we adjust the identity following Caliendo et al. (2018) to account for international trade and the value of gross operating surplus. After the adjustment, we compute the labor share and other input shares. We average them over five years, 2011-15. For the production technology of residential stocks, we set $\chi = 0.35$ based on labor compensation in the construction sector.

Gravity of trade. The regional trade in the model takes the form of a gravity equation. We assume that the regional trade costs are given by:

$$\ln \tau^s_{int} = \bar{\delta} + \varpi_s \ln \text{dist}_{in} + \delta^s_{int}(\tau)$$

where dist_{in} is geographical distance between n and i in kilometers and $\delta^s_{int}(\tau)$ is other factors that are orthogonal to other characteristics. Given this, trade values take the form of:

$$\ln X^s_{int} = \mathbb{D}^s_{it} + \mathbb{O}^s_{nt} - \theta_s \varpi_s \ln \text{dist}_{in} + \delta^s_{int} \tag{D.1}$$

where $\mathbb{D}^s_{it}$ factors destination characteristics and $\mathbb{O}^s_{nt}$ factors origin characteristics, respectively. Therefore, the coefficient estimated in the restricted gravity (D.1) gives information about $\theta_s \varpi_s$ that is a composite of Fréchet shape parameter ($\theta_s > 1$) and industry specific parameter for in trade costs, ϖ_s.

For commodities, we estimate (D.1) for $\theta_s \varpi_s$ using U.S. Commodity Flow Survey in 2012. As we cannot go back to the past, we only use cross sectional data. Once we obtain the estimate, we compute Fréchet shape parameter θ_s given ϖ_s. We assign the value of ϖ_s for commodities based on literature. Ramondo et al. (2016) proposed the value of trade cost elasticity with respect to distance, 0.27, for international trade. This value is close to the estimates in Hummels (2001). Further, Eaton and Kortum (2002) use the relationship between international trade and prices to estimate the Fréchet shape parameter 8.28 and coefficient of gravity equation such that 1.10. This implies the trade cost elasticity is around 0.13. Our analysis is the domestic trade; therefore, we use the lower value of the cost elasticity $\varpi_s = 0.125 = 1/8$ for all sectors in both manufacturing and services.

For the service sectors, we do not have direct observation of bilateral trade values. Therefore, we rely on estimates by Anderson et al. (2014). For non-tradables (i.e., retail), we set ∞ for the trade cost elasticity and Fréchet parameter is set to be 5.0, which is in around the middle of estimates for trade elasticities. Table D.1 summarizes numbers. The values of trade elasticity are in the range of estimates from the trade literature (Head and Mayer 2014, Simonovska and Waugh 2014). In addition, manufacturing shows a larger value of elasticity relative to services except for health and education services, which are consistent with findings in Gervais and Jensen (2019).

Labor mobility. In the model, a mass of workers who move from n to i satisfies:

$$\ln L^j_{int} - \ln L^j_{nnt} = -\varepsilon \ln D_{int} + \varepsilon(\ln B^j_{it} - \ln B^j_{nt}) + \varepsilon(\ln \mathcal{W}^j_{it} - \ln \mathcal{W}^j_{nt}) \tag{D.2}$$

Therefore, for the small difference in real income, the difference in labor mobility becomes:

$$\varepsilon = \frac{l^j_{int} - l^j_{nnt}}{(\tilde{w}^j_{it} - \tilde{p}^j_{it}) - (\tilde{w}^j_{nt} - \tilde{p}^j_{nt})} \tag{D.3}$$

where l^j_{int}, $\tilde{w}^j_{it}$ and $\tilde{p}^j_{it}$ are log of corresponding variables. Hence, ε reflects the elasticity of local labor supply across different locations to the real income, and we set $\varepsilon = 1.5$ that lies in the middle of the estimates in Fajgelbaum et al. (2019) for the U.S. economy.

Table D.1: Gravity coefficients estimated for commodities

(1) Industry	(2) $\theta_s \varpi_s$ (GC)	(3) $\theta_s \varpi_s$ (Route)	(4) θ_s	(5) Source
1. Food/Beverage/Tobacco	.990	.996	7.92	CFS 2012
2. Textile/Apparel	.824	.834	6.59	CFS 2012
3. Wood/Paper/Printing	1.13	1.134	9.04	CFS 2012
4. Chemical/Petro/Coal/ Nonmetalic	1.035	1.04	8.28	CFS 2012
5. Metal	1.029	1.036	8.23	CFS 2012
6. Machinery	.803	.812	6.42	CFS 2012
7. Electric/Computer	.626	.638	5.00	CFS 2012
8. Transport Equipment	.961	.966	7.68	CFS 2012
9. Miscellaneous Manufacture	.816	.828	6.53	CFS 2012
10. Transportation Service	.617	.617	4.94	Anderson et al. (2014)
11. Wholesale Trade	1.379	1.391	11.03	CFS 2012
12. Retail	∞	∞	5.0	–
13. FIRE	.678	.678	5.42	Anderson et al. (2014)
14. Health Service	1.42	1.42	11.36	Anderson et al. (2014)
15. Education and Legal	1.01	1.01	8.08	Anderson et al. (2014)
16. Communication Service	.297	.297	2.38	Anderson et al. (2014)
17. Other Services	.724	.724	5.79	Anderson et al. (2014)

Note: This table reports the estimated gravity coefficients and inferred trade elasticities for relevant industries. Column (2) uses the great circle distance for distance, and column (3) uses the route distance. In column (4), we compute trade elasticities based on estimates in column (2).

Now, we consider the friction in labor mobility. We assume that the friction takes the following form:

$$D_{int} = \text{dist}_{in}^{\varpi_M} F_{it}, \quad \forall i \neq n$$

where ϖ_M is a positive constant and F_{it} is a positive value that explains the migration barrier for workers who choose i. Mass of workers moving from n to i is:

$$L^j_{int} = (\text{dist}_{in})^{-\varepsilon\varpi_M} F_{it}^{-\varepsilon} \left(\frac{\kappa^j_{nt}}{\bar{U}^j_{nt}} \right)^{\varepsilon} (\mathcal{W}^j_{it})^{\varepsilon} L_{nt-1} \tag{D.4}$$

Taking logs, (D.4) can be written as:

$$\ln L^j_{int} = \mathbb{W}^j_{it} - \varepsilon\varpi_M \ln \text{dist}_{in} + \mathbb{H}^j_{nt} \tag{D.5}$$

where

$$\mathbb{W}^j_{it} \equiv \varepsilon \ln \mathcal{W}^j_{it} - \varepsilon \ln F_{it}, \quad \mathbb{H}^j_{nt} \equiv \varepsilon \ln \kappa^j_{nt} - \varepsilon \ln \bar{U}^j_{nt} + \ln L_{nt-1}$$

contain source location and industry characteristics and destination and industry characteristics, respectively.

We use (D.5) to obtain estimated value of $\varepsilon\varpi_M$. To this end, we need information on labor mobility between locations for workers in different sectors. We use ACS 5-year sample data between 2006-2010 and 2011-2015. The ACS data allows us to know the current location (county), previous location (county), and industry of workers in the sample. We extract workers in our sectors and map their locations to the CBSA level. Then, we focus on workers who moved between different CBSAs during the sample periods and compute average distances at the aggregation of the state level. Therefore, the final data contains the number of workers in each sector who move from state to state and the average distance of the mobility pattern. We construct the data for 5-year period, 2006-10, 2011-15 and a 10-year period, 2006-2015. Using the data, we estimate (D.5) by ordinary least squares (OLS). We replace $\mathbb{W}^j_{it}$ and $\mathbb{H}^j_{nt}$ by origin-sector indicators and destination-sector indicators, respectively.

Table D.2 shows the estimates of $\varepsilon\varpi_M$. The estimates are similar to the findings for intra-national migration elasticity to distance in Bryan and Morten (2019) for Indonesia. Compared to Allen and Arkolakis (2018) for migration cost in U.S. history, estimates are small. This difference arises from the different periods of our data. For the old period, it would be large because of the higher moving cost per unit of distance. Based on the results, our preferable value for migration elasticity is 0.75, and therefore we set $\varpi_M = 0.50$ in our analysis.

Table D.2: Coefficients estimated for workers mobility

	(1) Year 2006-10	(2) Year 2011-15	(3) Year 2006-15
ln distance	-.743	-.728	-.806
	(0.0296)	(0.0317)	(0.0282)
Observations	11,292	11,374	14,852

Note: Robust standard errors in parenthesis.

Industry choice of workers and persistent effect. We consider the parameters in labor supply, η and ϕ. We let $\mathbb{U}^j_{nt+1} \equiv \zeta_j^{1/\phi}\bar{U}^j_{nt+1}$. Then, we use the structural equations in our model. Using migration costs (D.2), our model derives:

$$\mathbb{U}^j_{it+1} = \left(\sum_{\ell} \left(\text{dist}_{\ell i}^{-\varepsilon\varpi_M} \frac{L^j_{\ell t+1}}{\sum_n \left(\text{dist}_{\ell n}^{-\varepsilon\varpi_M} \frac{(L^j_{nt})^{\eta}(\mathbb{U}^j_{nt+1})^{\phi}}{\sum_k (L^k_{nt})^{\eta}(\mathbb{U}^k_{nt+1})^{\phi}} (\mathbb{U}^j_{nt+1})^{-\varepsilon} L_{nt} \right)} \right) \right)^{1/\varepsilon} \tag{D.6}$$

for every i and j. This is labor mobility clearing condition. (D.6) gives the relationship between employment $\{L^j_{it+1}\}$, $\{L^j_{it}\}$, geographical distance and $\{\mathbb{U}^j_{it+1}\}$.

First, we use the above parameters (ε, ϖ_M) and guess two key parameters (ϕ, η). Implementing the observation of employment $\left(\{L^j_{it+1}\}, \{L^j_{it}\}\right)$, we solve $N \times (K+1)$ equations for $\{\mathbb{U}^j_{it+1}\}$ as a fixed point of (D.6). We denote this as $\widehat{\mathbb{U}}^j_{it+1}$. Then, we compute the inferred probabilities in industry choice,

$$\widehat{\kappa}^j_{nt+1} = \frac{\left(L^j_{nt}\right)^{\eta}\left(\widehat{\mathbb{U}}^j_{nt+1}\right)^{\phi}}{\sum_k \left(L^k_{nt}\right)^{\eta}\left(\widehat{\mathbb{U}}^k_{nt+1}\right)^{\phi}} \tag{D.7}$$

where we use employment in observation, L^j_{nt}. Further, by construction, we have:

$$\bar{U}^j_{it+1} = \left(\sum_n \text{dist}_{ni}^{-\varepsilon\varpi_M} \left(B^j_{nt+1} \mathcal{W}^j_{nt+1} / F_{nt}\right)^{\varepsilon} \right)^{1/\varepsilon} \tag{D.8}$$

Therefore, we can write:

$$\mathbb{U}^j_{it+1} = \left(\sum_n \text{dist}_{ni}^{-\varepsilon\varpi_M} \left(\widetilde{T}^j_{nt}\right)^{\varepsilon} \right)^{1/\varepsilon} \tag{D.9}$$

where we let

$$\widetilde{T}_{nt}^{j} \equiv \frac{B_{nt}^{j}\mathcal{W}_{nt}^{j}}{\zeta_{j}^{1/\phi}F_{nt}}$$

We define:

$$\widetilde{\mathbb{U}}_{t+1} \equiv \left\{\left(\mathbb{U}_{it+1}^{j}\right)^{\varepsilon}\right\}, \quad \mathbb{D} \equiv \left\{\text{dist}_{ni}^{-\varepsilon\varpi_M}\right\}, \quad \mathbb{T}_{t+1} \equiv \left\{\left(\widetilde{T}_{nt}^{j}\right)^{\varepsilon}\right\}$$

$\widetilde{\mathbb{U}}_{t+1}$ is $N \times (K+1)$ matrix of average utility conditional on industry choice, $\mathbb{D}$ is $N \times N$ matrix of distances, and $\mathbb{T}_{t+1}$ is $N \times (K+1)$ matrix of adjusted real income by migration cost. (D.9) implies that we can compute $\widehat{\widetilde{T}}_{\ell,t}^{s}$ by:

$$\widehat{\mathbb{T}}_{t+1} = \left(\mathbb{D}^{\top}\right)^{-1}\widehat{\widetilde{\mathbb{U}}}_{t+1} \tag{D.10}$$

where $\widehat{\widetilde{\mathbb{U}}}_{t+1}$ is matrix $\widetilde{\mathbb{U}}_{t+1}$ by substituting $\{\widehat{\mathbb{U}}_{it+1}^{j}\}$. After we compute this, we derive the model inferred location choice probabilities:

$$\widehat{\lambda}_{int+1}^{j} = \left(\text{dist}_{in}^{-\varpi_M} \times \frac{\widehat{\widetilde{T}}_{it+1}^{j}}{\widehat{\mathbb{U}}_{nt+1}^{j}}\right)^{\varepsilon} \tag{D.11}$$

Combining (D.7) and (D.11), we obtain the mobility of workers between two locations during period t and $t+1$:

$$\widehat{L}_{int+1} = \sum_{j}\widehat{\lambda}_{int+1}^{j}\widehat{\kappa}_{nt+1}^{j}L_{nt} \tag{D.12}$$

This is the labor mobility from n to i for any particular generation $t+1$ predicted in the model. Using (D.12), we compute $\widehat{\vartheta}_{int+1} = \widehat{L}_{int+1}/\sum_{\ell\neq i}\widehat{L}_{\ell nt+1}$ for $i \neq n$, which is the predicted pattern of migration from location n in the model.

In turn, we exploit IRS county-to-county migration data and aggregate the flow of people to the CBSA pairs which we use. We process this for two time periods, 1990-2000 and 2000-2010. The period 1990-2000 corresponds to the movement of workers in generation 2000, while the period 2000-2010 corresponds to the movement of workers in generation 2010. We compute $\vartheta_{int+1} = L_{int+1}/\sum_{\ell\neq n}L_{\ell nt+1}$ where L_{int+1} is the migration from source n to destination i. This is the pattern of labor mobility given the source location.

Then, we argue that the pattern of emigration in the data is equal to the pattern predicted in the model. Namely, we consider the following moment condition:

$$\mathbb{E}\left[\left(\vartheta_{in,t+1} - \widehat{\vartheta}_{in,t+1}\right) \times \mathbb{1}_{in}\right] = 0$$

The underlying assumption for this is that any errors between the observed pattern of migration and the migration pattern predicted in the model are unrelated to the level of distances within the same range of distances. In particular, we define 6 ranges of distances between two locations, and we use the moment condition. Then, we obtain the parameter $\phi = 2.50$ and $\eta = 0.80$ used in our analysis.

D.3 Calibration of Fundamentals

D.3.1 Inversion of Fundamentals in the Steady State Equilibrium

We compute the baseline level of the environment as we need to obtain the endogenous variables for the baseline economy that we cannot directly observe in the data at the disaggregated level. We drop the subscript t for the steady state equilibrium. Suppose that we have data for wage

$\{w_i^s\}$, workers $\{L_i^s\}$ and price of housing $\{p_i^0\}$ in the steady state. Then, we obtain values of fundamentals in space: (i) migration cost adjusted amenity; (ii) fundamental productivity; (iii) fundamental features in the development of residential stocks. We explain the procedures and relevant results step by step. We suppose that economy is in the steady state in 2010.

Step 1: Development and income. In the steady state, we obtain:

$$H_i = \nu_i^{1/\chi}(1-\bar{h}_i)^{(1-\chi)/\chi} L_i^0 \tag{D.13}$$

and we also derive

$$\widetilde{\nu}_i \equiv \nu_i (1-\bar{h}_i)^{1-\chi} = \exp\left(\chi\left(-\ln\chi + \ln w_i^0 - \ln p_i^0\right)\right) \tag{D.14}$$

We use $\chi = 0.35$. We also implement the price of housing in 2010 into $\{p_i^0\}$. Our data for the housing price comes from Federal Housing Finance Agency (FHFA). We exploit the Hosing Price Index (HPI) of the all-transactions index across CBSAs. We also implement wage of sector 0 (i.e., construction sector) in 2010 for $\{w_i^0\}$. Then, (D.14) gives value of fundamental efficiency, $\{\widetilde{\nu}_i\}$, for CBSAs.

Step 2: Inversion of overall endogenous productivity. We solve for overall productivity in location i and sector s for tradables, Z_i^s. Guess the vector of overall productivity, $\{Z_i^s\}$. Letting $\tau_{in}^s \equiv \text{dist}_{in}^{\omega_s}$, we compute price vector of tradables:

$$\Gamma_s^{\theta_s}\left(p_i^s\right)^{-\theta_s} = \sum_n \left(\left(\tau_{in}^s\right)^{-\theta_s}\left(Z_n^s\right)^{\theta_s}\left(\left(w_n^s\right)^{\beta_s}\prod_j\left(p_n^j\right)^{\beta_{sj}}\right)^{-\theta_s}\right) \tag{D.15}$$

Solution for this is $\{p_i^s\}$. Once we have $\left(\{p_i^s\}, p_i^0, \{W_i^s\}\right)$, we solve the following $N \times N \times (K+1)$ dimensional fixed point system of equations:

$$\left(P_i^s\right)^{1-\sigma} = \sum_j \alpha_j^{\sigma-1}\left(p_i^j\right)^{1-\sigma}\left(\frac{W_i^s}{\mathcal{P}_i^s}\right)^{\mu_j-1} \tag{D.16}$$

for non-homothetic price index, $\{P_i^s\}$. Now, we use the market clearing condition. The market clearing condition for final goods and labor market clearing condition implies:

$$Z_i^s = \left(\frac{w_i^s L_i^s}{\beta_s}\right)^{1/\theta_s}\left(\left(w_i^s\right)^{\beta_s}\prod_j\left(p_i^j\right)^{\beta_{sj}}\right)\left(\sum_n\left(\tau_{ni}^s p_n^s\right)^{-\theta_s}\sum_j\left(\beta_{js}\frac{w_n^j L_n^j}{\beta_j} + \alpha_s^{\sigma-1}\left(p_n^s\right)^{1-\sigma}\left(P_n^j\right)^{\sigma}\left(\frac{W_n^j}{P_n^j}\right)^{\mu_s} L_n^j\right)\right)^{-1/\theta_s} \tag{D.17}$$

We solve (D.17) for $\{Z_i^s\}$. The inner loop calculation for this procedure gives inferred overall productivity, $\{Z_i^s\}$, and other endogenous variables used in the inner loop, $\left(\{p_i^s\}, \{P_i^s\}\right)$.

Step3: Inversion of amenities and labor mobility. Now, we consider labor mobility. Once the economy reaches the steady state, the mass of workers in the local labor market becomes constant. Yet, we have the move of workers due to idiosyncratic shocks.

We have three fundamentals here. First, we have fundamental amenity, $\{B_i^s\}$. Second, as we have introduced migration barrier in each location in (D.2), $\{F_i\}$. These two fundamentals decide the exogenous gains for workers who choose the destination, and it is impossible to isolate them. Further, we have another fundamental in the industry choice, $\{\zeta_s\}$. Therefore, we consider the construction of inferred fundamental for location choice,

$$\Omega_i^s = B_i^s \times \frac{1}{F_i} \times \zeta_s^{1/\phi} \tag{D.18}$$

that conflates them. We begin with the guess of $\{\Omega_i^s\}$.

Letting $\widetilde{D}_{in} \equiv \text{dist}_{in}^{-\varpi_M}$ based on estimation in Subsection D.2, we compute the adjusted average real income:

$$\bar{\mathbb{U}}_n^s = \left(\sum_i \left(\Omega_i^s \widetilde{D}_{in} \frac{W_i^s}{\mathcal{P}_i^s}\right)^\varepsilon\right)^{1/\varepsilon} = \zeta_s^{1/\phi} \bar{U}_n^s \tag{D.19}$$

We also compute the probability of labor mobility conditional on the sector choice and the probability of sectoral choice:

$$\lambda_{in|s} = \left(\frac{\Omega_i^s \widetilde{D}_{in}}{\bar{\mathbb{U}}_n^s}\left(\frac{W_i^s}{\mathcal{P}_i^s}\right)\right)^\varepsilon, \quad \kappa_n^s = \frac{\left(L_n^s\right)^\eta \left(\bar{\mathbb{U}}_n^s\right)^\phi}{\sum_j \left(L_n^j\right)^\eta \left(\bar{\mathbb{U}}_n^j\right)^\phi} \tag{D.20}$$

Then, we use labor mobility condition:

$$L_i^s = \sum_n \lambda_{in|s} \varsigma_n^s L_n \tag{D.21}$$

Plugging the above equations into this yields:

$$\Omega_i^s = \left(\frac{1}{L_i^s}\sum_n \left(\frac{\widetilde{D}_{in}}{\bar{\mathbb{U}}_n^s}\left(\frac{W_i^s}{\mathcal{P}_i^s}\right)\right)^\varepsilon \frac{\left(L_n^s\right)^\eta \left(\bar{\mathbb{U}}_n^s\right)^\phi}{\sum_j \left(L_n^j\right)^\eta \left(\bar{\mathbb{U}}_n^j\right)^\phi} L_n\right)^{-1/\varepsilon} \tag{D.22}$$

In the right-hand-side, we use (D.19) inside the loop. Inner loop for this step gives inferred fundamental amenity, $\{\Omega_i\}$ and other endogenous variables. In particular, we derive:

$$L_{in}^s = \lambda_{in|s} \kappa_n^s L_n \tag{D.23}$$

$\{L_{in}^s\}$ is mass of workers in sector s who move from n to i.

Step4: Inversion of productivity. As a last step, we consider the inversion of fundamental productivity and calibration of parameter ρ. In the steady state, overall productivity satisfies:

$$Z_i^s = A_i^s \left(\sum_n L_{in}^s Z_n^s\right)^\rho \left(L_i^s\right)^{\gamma_s} \tag{D.24}$$

Therefore, the exogenous fundamental productivity is:

$$\ln A_i^s = \ln Z_i^s - \rho \ln \left(\sum_n L_{in}^s Z_n^s\right) - \gamma_s \ln L_i^s \tag{D.25}$$

We implement overall productivity $\{Z_i^s\}$ in Step 2, inferred labor mobility $\{L_{in}^s\}$ in Step 3 and employment in data $\{L_i^s\}$ and parameters $\{\gamma_s\}$ into this. To estimate ρ, we use the following moment conditions:

$$\mathbb{E}\left[\left(\ln A_i^s - \frac{1}{N}\sum_n \ln A_n^s - \frac{1}{S}\sum_k \ln A_i^k\right) \times \mathbb{I}_g\right] = 0, \quad g \in \mathbb{G}_0, \mathbb{G}_1, \cdots, \mathbb{G}_P \tag{D.26}$$

where $\mathbb{I}_g$ is an indicator that the labor market potential of location i is in the group of g. The group of locations is defined by the accessibility of the location i. We ordered locations by the sum of population in other places with an inverse of bilateral migration cost as weights. Namely, for location i and sector s, we compute the measure $\sum_{n \neq i} \widetilde{D}_{in}^\varepsilon L_n^s$ to define the group of location and sector pairs based. The moment conditions assume that the location and sector specific exogenous part after eliminating averages is not systematically related to the labor market access of the location as the spatial dependence of productivity is captured by the endogenous terms in (D.25) through labor mobility. We use (D.26) and search parameter ρ that minimize the distances of the moment conditions. The estimated ρ that minimizes the objective function is given by the dashed line, $\widehat{\rho} = 0.0284$.

D.3.2 Computing Past Fundamentals

Our aim is solving the model for time-variant environment of the economy conditional on our information about the local labor markets. To this end, we compute the path of $\{A_{it}^s\}$. In period $t = 2010$, we assume $A_{it}^s = A_i^s$ that is derived in (D.25) and it is unchanged after then. So, we compute the path of $\{A_{iT}^s\}_{T=t-1,t-2,\cdots}$ back to the previous periods. For fundamental amenities, our interests are dynamics of residential amenity $\{B_{it}^s\}$ and migration barrier $\{F_{it}\}$. Our observation over periods is the equilibrium wage and employment in 2000, 1990 and 1980, $\{w_{it}^s\}$ and $\{L_{it}^s\}$. Given other exogenous environments and parameters discussed above, they are sufficient to compute the pattern of fundamental productivity and amenities in the past, starting from the steady state equilibrium.

Step1: Housing and land market clearing conditions. Given $\left(\{w_{it-1}^0\}, \{L_{it-1}^0\}\right)$, zero profit condition and distribution of land rent implies:

$$R_{it-1} = \frac{1-\chi}{\chi} w_{it-1}^0 L_{it-1}^0, \quad W_{it-1}^s = \left(1 + \frac{R_{it-1}}{\sum_j w_{it-1}^j L_{it-1}^j}\right) w_{it-1}^s \tag{D.27}$$

Using zero profit condition, in the steady state equilibrium (i.e., $t = 2010$) or any period t, we compute the stock of residential stocks such that:

$$H_{it} = \frac{1}{\chi} \frac{w_{it}^0 L_{it}^0}{p_{it}^0} \tag{D.28}$$

Once we obtain this, we compute the residential stock in the previous period that solves:

$$\ln H_{it-1} = \frac{1}{1-\chi} \left(\ln H_{it} - \ln \widetilde{\nu}_i - \chi \ln L_{it}\right) \tag{D.29}$$

where we use $\{\widetilde{\nu}_i\}$ in the subsection D.3.1. Then, market clearing condition leads to price in period $t-1$:

$$p_{it-1}^0 = \frac{1}{\chi} \frac{w_{it-1}^0 L_{it-1}^0}{H_{it-1}} \tag{D.30}$$

This procedure obtain the path of $\left(\{p_{it-1}^0\}, \{H_{it-1}\}, \{R_{it-1}\}, \{W_{it-1}^s\}\right)$ in equilibrium that are not directly observable.

Step2: Overall productivity path. To derive the overall productivity in the past, we guess the path of productivity, $\{\mathrm{d} \ln Z_{it}^s\}$. Therefore, we guess $\{Z_{it-1}^s\}$, given pre-determined $\{Z_{it}^s\}$. Then, we compute price $\{p_{it-1}^s\}$ that solve:

$$\mathrm{d} \ln p_{it}^s \equiv \ln p_{it}^s - \ln p_{it-1}^s = -\frac{1}{\theta_s} \ln \left(\frac{\sum_n \left(\tau_{in}^s \left(w_{nt}^s\right)^{\beta_s} \prod_j \left(p_{nt}^j\right)^{\beta_{sj}}\right)^{-\theta_s} \left(Z_{nt}^s\right)^{\theta_s}}{\sum_n \left(\tau_{in}^s \left(w_{nt-1}^s\right)^{\beta_s} \prod_j \left(p_{nt-1}^j\right)^{\beta_{sj}}\right)^{-\theta_s} \left(Z_{nt-1}^s\right)^{\theta_s}} \right) \tag{D.31}$$

and we compute the trade pattern $\{\pi_{int-1}^s\}$ such that:

$$\mathrm{d} \ln \pi_{int}^s \equiv \ln \pi_{int}^s - \ln \pi_{int-1}^s = \theta_s \left(\mathrm{d} \ln Z_{nt}^s - \mathrm{d} \ln p_{it}^s - \mathrm{d} \ln w_{nt}^s + \sum_j \beta_{sj} \mathrm{d} \ln p_{nt}^j\right) \tag{D.32}$$

Given income and price in period $t-1$, $\left(\{p^s_{it-1}\}, \{W^s_{it-1}\}\right)$, we solve for aggregate price index $\{\mathcal{P}^s_{it-1}\}$ as in (D.16). Then, we use the static equation of market clearing conditions, as in (D.17), to solve for the overall productivity $(\{\widehat{Z}^s_{it-1}\})$ that rationalize observed wage and number of workers as an equilibrium.

Step3: Casting the workers' move and path of amenities. The procedures Step 1 and 2 allow us to compute the spatial distribution of prices, real income and overall productivity, starting from the steady state level set to the year 2010. Next, we use the model structure forward from the initial period. This allows us to derive the path of location attractiveness. We start from the guess of overall attractiveness of location and sector, $\Omega^j_{i,t}$ as in Subsection D.3.1: $\Omega^j_{i,t} \equiv B^j_{i,t}\zeta_j^{1/\phi}/M_i$. This overall amenity becomes large when the value of utility benefit from residential amenity for workers in location i ($B^j_{i,t}$) is high, migration barrier of location i (M_i) is small and sector level taste parameter (ζ_j) is large for workers in the sector.

Guess Ω^s_{it}. Given income $\{W^s_{it}\}$ derived in Step1 and aggregate price index $\{P^s_{it}\}$ derived in Step2, we compute the average real income

$$\widehat{\mathbb{U}}^s_{nt} = \left(\sum_i \left(\widetilde{D}_{in}\Omega^s_{it}\frac{W^s_{it}}{P^s_{it}}\right)^{\varepsilon}\right)^{1/\varepsilon} \tag{D.33}$$

Then, we compute

$$\widehat{\Omega}^s_{it} = \left(\frac{1}{L^s_{it}}\sum_n \left(\frac{\widetilde{D}_{in}}{\widehat{\mathbb{U}}^s_{nt}}\left(\frac{W^s_{it}}{P^s_{it}}\right)\right)^{\varepsilon} \frac{\left(L^s_{nt-1}\right)^{\eta}\left(\widehat{\mathbb{U}}^s_{nt}\right)^{\phi}}{\sum_j \left(L^j_{nt-1}\right)^{\eta}\left(\widehat{\mathbb{U}}^j_{nt}\right)^{\phi}} L_{nt-1}\right)^{-1/\varepsilon} \tag{D.34}$$

We update Ω^j_{it} until $\|\widehat{\Omega}^j_{it} - \Omega^j_{it}\| < \varepsilon$ for sufficient small number ε and appropriate norm $\|\cdot\|$.

This procedure allows us to cast the workers' choice across locations and sectors predicted in the model. This is essential as an overidentification test to assess the performance of our model for workers' choice. In particular, we compute two probabilities:

$$\widehat{\lambda}^s_{int} = \left(\frac{\widehat{\Omega}^s_{it}\widetilde{D}_{in}}{\widetilde{\mathbb{U}}^s_{nt}}\left(\frac{W^s_{it}}{P^s_{it}}\right)\right)^{\varepsilon}, \quad \text{with} \quad \widehat{\mathbb{U}}^s_{nt} = \left(\sum_i \left(\widetilde{D}_{ni}\widehat{\Omega}^s_{it}\frac{W^s_{it}}{P^s_{it}}\right)^{\varepsilon}\right)^{1/\varepsilon} \tag{D.35}$$

and

$$\widehat{\kappa}^s_{nt} = \frac{\left(L^s_{nt-1}\right)^{\eta}\left(\widehat{\mathbb{U}}^s_{nt}\right)^{\phi}}{\sum_j \left(L^j_{nt-1}\right)^{\eta}\left(\widehat{\mathbb{U}}^j_{nt}\right)^{\phi}} \tag{D.36}$$

where we use pre-period population in data (L^s_{it-1}). We lastly compute

$$\widehat{L}^s_{int} = \sum_n \widehat{\lambda}^s_{int}\widehat{\varsigma}^s_{nt}L_{nt-1} \tag{D.37}$$

where L_{nt-1} is total number of workers in data for previous generation. (D.37) is predicted move of workers for generation t.

Step 4: Fundamental productivity. For the initial period, we set $A^s_{it} = Z^s_{it}$. In our setting, it is applied for 1980. For other period, we compute

$$\ln \widehat{A}^s_{it} = \ln \widehat{Z}^s_{it} - \widehat{\rho}\ln\left(\sum_n \widehat{L}^s_{int}\widehat{Z}^s_{nt-1}\right) - \gamma_s \ln L^s_{it} \tag{D.38}$$

where $\widehat{\rho}$ is obtained in the subsection D.3.1 and $\{\widehat{Z}^s_{it}\}$ are computed in Step2.

E Calibration Results

This section presents the results of calibration that we explained in the previous section. Subsection E.1 shows the results for an inversion of development, amenities and productivity. We also compute TFP. Subsection E.2 shows the welfare and intergenerational mobility in the baseline.

E.1 Inverted Environment

Housing Prices and Development Efficiency. We can gauge our model specification in (D.29) and (D.30) by comparing the predicted value of $\{\widehat{p}^0_{it}\}$ in the past. Among 395 CBSAs in our calibration, FHFA data for housing prices are limited for the past years. Therefore, we compare housing prices predicted in the model for past years, 1980 and 1990, and those in data for a limited number of CBSAs in the supplementary material.

Amenities. Using the local data, we obtain the local amenities for workers, Ω^s_{it}. For each year, 2010, 2000 and 1990, Table E.1 reports the mean and standard deviation of the logarithm of the amenity vector across different sectors. We find the difference in their variations across industries, and the standard deviation becomes large in the last period compared to the previous periods. Large value of amenity in location i and sector s (Ω^s_{it}) is associated with large number of workers of sector s. Therefore, the average of Ω^s_{it} at the CBSA level is related to the total size of CBSA. See the supplementary material for the relationship.

Table E.1: Summary of Local Amenities $\{\Omega^s_{i,t}\}$

	2010		2000		1990	
Industry	Mean	S.D.	Mean	S.D.	Mean	S.D.
0. Construction	-0.004	1.054	0.028	0.840	-0.004	0.905
1. Food/Beverage/Tobacco	0.006	0.944	0.025	0.770	0.022	0.881
2. Textile/Apparel	-0.047	1.082	-0.026	0.883	0.018	0.938
3. Wood/Paper/Printing	0.014	1.002	0.007	0.813	0.027	0.858
4. Chemical/Petro/Coal/ Nonmetalic	0.007	1.007	0.026	0.786	-0.002	0.831
5. Metal	0.036	0.989	0.058	0.805	0.028	0.864
6. Machinery	0.003	1.010	-0.033	0.823	0.014	0.879
7. Electric/Computer	0.013	0.998	-0.036	0.867	-0.032	0.928
8. Transport Equipment	0.026	0.916	-0.007	0.788	0.003	0.834
9. Miscellaneous Manufacture	-0.006	1.029	0.004	0.827	0.035	0.841
10. Transportation Service	-0.015	1.016	-0.043	0.885	-0.002	0.893
11. Wholesale Trade	0.023	0.928	-0.001	0.784	0.000	0.885
12. Retail	-0.016	1.047	0.022	0.788	-0.008	0.913
13. FIRE	0.013	0.962	0.012	0.752	-0.024	0.895
14. Health Service	-0.023	0.998	0.004	0.741	-0.001	0.843
15. Education and Legal	0.008	1.008	-0.019	0.852	-0.013	0.920
16. Communication Service	-0.035	1.073	-0.008	0.856	-0.049	0.998
17. Other Services	-0.005	1.006	-0.013	0.863	-0.012	0.934

Productivity. Step 2 in the subsection D.3.2 yields overall productivity (Z^s_{it}) for past years: 1980, 1990, 2000 and 2010. In addition, we obtain trade patterns (π^s_{int}). Using them, we can compute TFP for each sector and location as we discussed in the subsection C.1, $\ln \delta_{it}^s$. In Table E.2, we report the standard deviation of the measured TFP and inverted fundamental productivity across CBSAs. The fundamental productivity shows the large spatial variation relative to TFP. This implies that the covariance of the import penetration (π_{iit}^s) and fundamental productivity is significant. Intuitively, firms in a city demand for own products more when the location exhibits high fundamental productivity.

Table E.2: Spatial Variation of TFP and Fundamental Productivity

	1980		1990		2000		2010	
Industry	S.D.(δ_i^s)	S.D.(A_i^s)	S.D.(δ_i^s)	S.D.(A_i^s)	S.D.(δ_i^s)	S.D.(A_i^s)	S.D.(δ_i^s)	S.D.(A_i^s)
1. Food/Beverage/Tobacco	.037	.050	.042	.102	.051	.098	.055	.103
2. Textile/Apparel	.077	.115	.096	.102	.100	.136	.164	.225
3. Wood/Paper/Printing	.040	.044	.044	.115	.053	.108	.059	.111
4. Chemical/Petro/Coal/Nonmetalic	.035	.044	.038	.120	.052	.114	.057	.108
5. Metal	.045	.053	.042	.114	.050	.110	.093	.144
6. Machinery	.060	.107	.073	.105	.087	.108	.082	.111
7. Electric/Computer	.087	.209	.112	.112	.159	.143	.178	.179
8. Transport Equipment	.044	.060	.047	.111	.054	.094	.061	.097
9. Miscellaneous Manufacture	.090	.131	.078	.111	.094	.121	.105	.124
10. Transportation Service	.067	.207	.063	.159	.067	.150	.070	.155
11. Wholesale Trade	.038	.038	.047	.153	.058	.148	.072	.156
12. Retail	.045	.045	.059	.269	.068	.261	.060	.270
13. FIRE	.054	.158	.082	.164	.102	.158	.103	.145
14. Health Service	.055	.056	.066	.150	.060	.142	.068	.148
15. Education and Legal	.081	.093	.097	.160	.100	.160	.110	.142
16. Communication Service	.064	.615	.073	.120	.092	.157	.103	.191
17. Other Services	.102	.183	.119	.128	.171	.156	.142	.141

Note: This table reports the standard deviation of measured TFP ($\delta_{i,t}^s$) and fundamental productivity ($A_{i,t}^s$) for any particular year and industry.

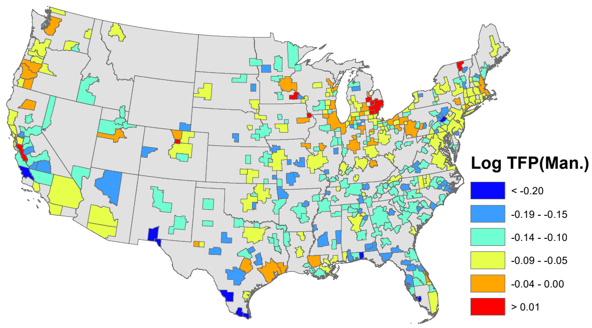
Having TFP of each industry, we compute the TFP aggregated to large sector level: manufacturing and services. We compute TFP of aggregated level:

$$\delta_{it}^K = \sum_{j \in K} \frac{X_{it}^j}{\sum_{k \in K} X_{it}^k} \delta_{it}^j \tag{E.1}$$

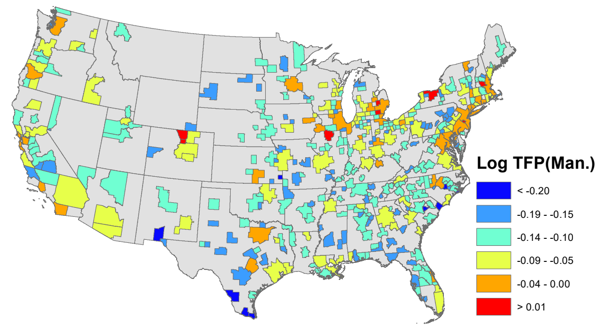
where K is aggregate level of sector and X_{it}^j is value of production of sector j in location i. We compute two aggregate sectors, the manufacturing sector and the services sector, for K. Figure E.1 show log of TFP of manufacturing sector in different period: 1980, 1990, 2000 and 2010. Red colored areas show high TFP for the manufacturing sector, while blue colored CBSAs exhibit low TFP for the manufacturing sector. As we can see in the maps, cities around the Rust Belt show persistence in their relatively high productivity in manufacturing, while the South and East coast areas show growth in productivity in manufacturing. These differences across space reflect the set of industries in the manufacturing sector across different cities.

In turn, figure E.2 show the log of TFP of the service sector in different periods. Red colored areas show high TFP for the service sector, while blue colored CBSAs exhibit low TFP. We can see the TFP growth over time in the U.S. economy with clustering. Throughout time, the TFP of services grows in large cities, while there are variations across regions. From 1980 to 1990, the services grow in cities on the East coast and the West coast. The period 1990 to 2000 exhibits

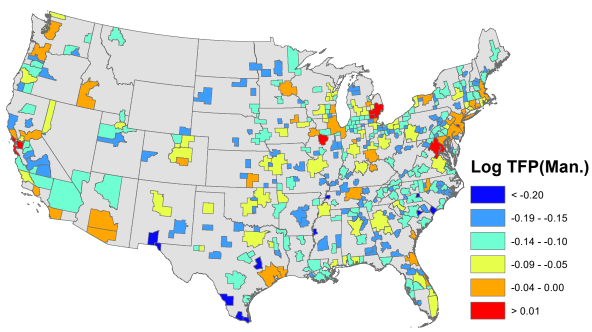
Figure E.1: TFP of Manufacturing Sector



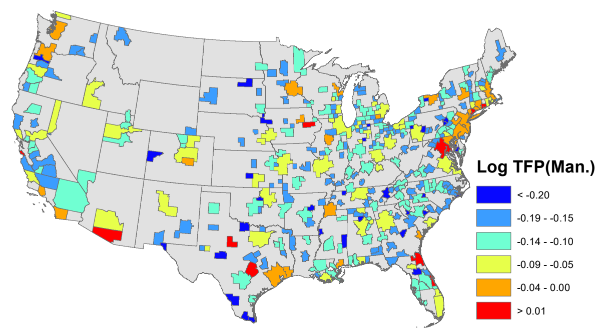
(a) 1980



(b) 1990



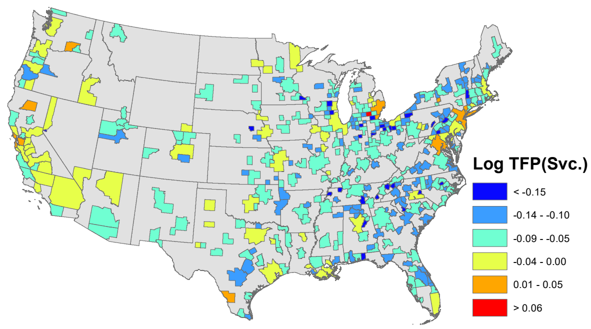
(c) 2000



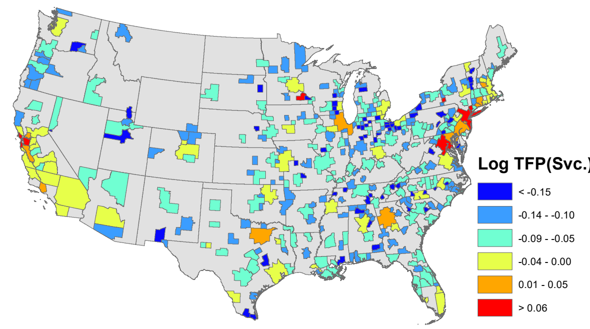
(d) 2010

growth of TFP in the South. In the last period, 2000-10, the persistent growth in these areas led to the country's service growth.

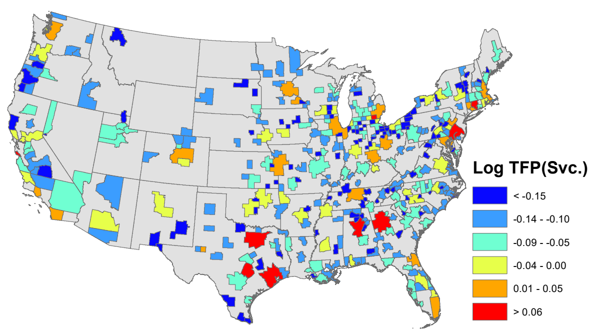
Figure E.2: TFP of Services Sector



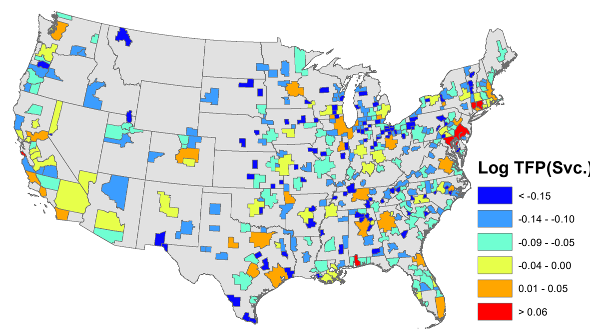
(a) 1980



(b) 1990



(c) 2000

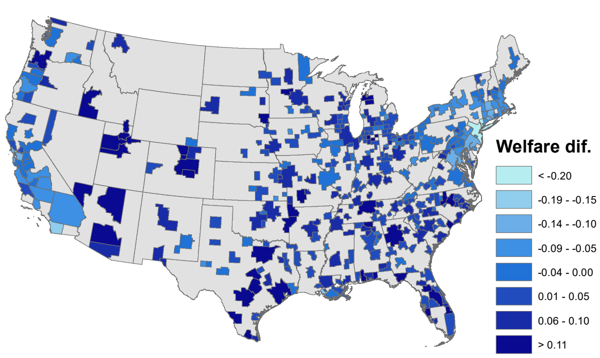


(d) 2010

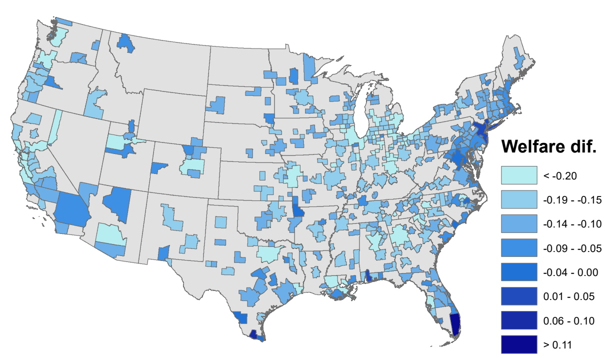
E.2 Welfare and Upward Mobility

Figure E.3 displays the distribution of welfare differences between individuals who have the same origin of CBSA. Panel (a) shows the welfare difference between generation 2000 and 1990, and panel (b) is for generation 2010 and 2000. Figures E.4 show the distribution of welfare changes. Most locations exhibit a welfare decline from 2000 to 2010. This reflects the lower wage growth and higher increases in housing prices during the period, while the effects show large variation across locations.

Figure E.3: Welfare Differences



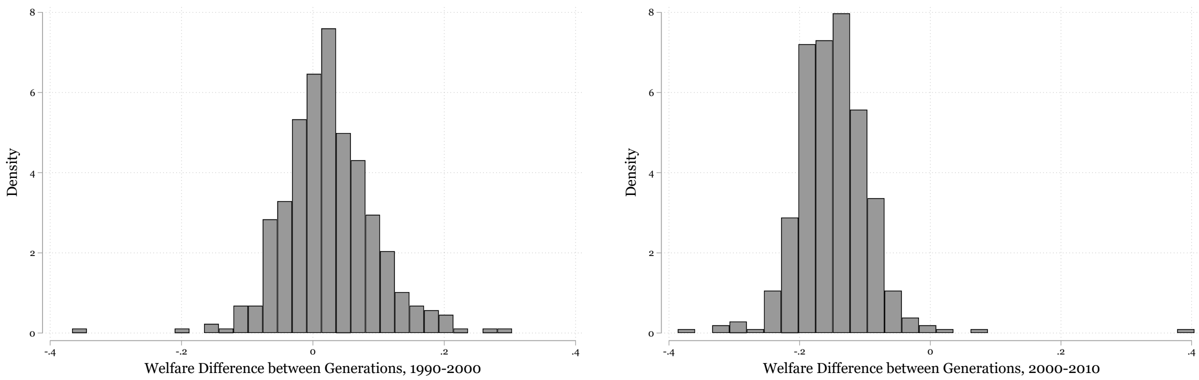
(a) $\mathrm{d}\ln V_{i,2000}$



(b) $\mathrm{d}\ln V_{i,2010}$

Note: These figures show the spatial pattern of welfare differences between generations.

Figure E.4: Distribution of Welfare Dynamics

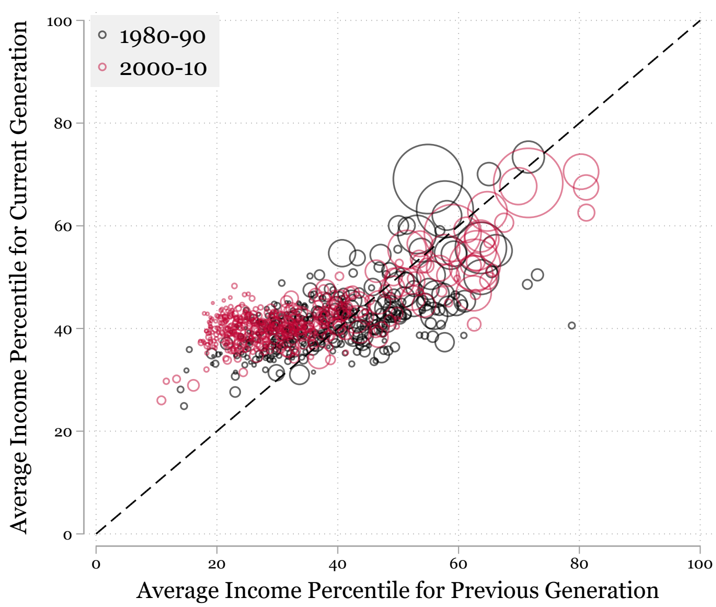


(a) 1990-2000

(b) 2000-2010

Note: These figures show the distribution of the measure of welfare differences between generations.

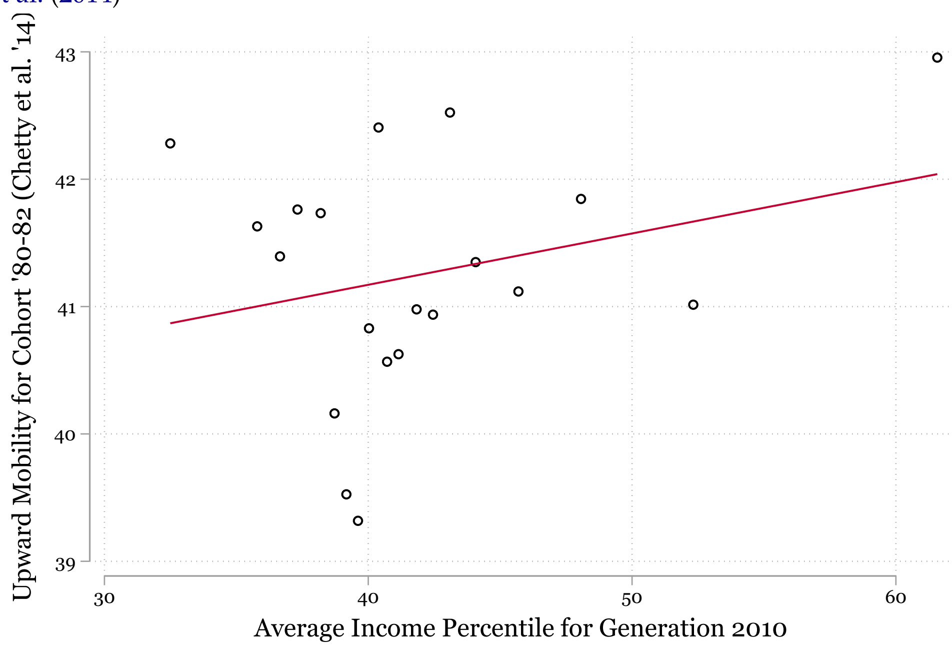
Figure E.5: Average Income Percentile of Individuals



Next, we see the upward mobility for individuals of each generation. Figure E.5 shows, for each CBSA, the income percentile for generation t working in the CBSA and the income percentile for generation $t+1$ who have origin in the CBSA. For each CBSA, the horizontal axis shows the average income percentile of workers (i.e., old generations) in the country; the vertical axis shows the average income percentile of individuals in the next generation. The black colored ones show the relationship for generations 1980 and 1990, while red colored ones show that for 2000 and 2010. Each circle represents the size of generation 1980 and 2000 respectively, and the dashed line is the 45-degree line. Therefore, locations above the reference line show upward mobility of the generation compared to their previous generation, while those below the line are the places with relatively low upward mobility. From this figure, we find that large CBSAs exhibit lower upward mobility in 2000-10 compared to 1980-90, which leads to lower upward mobility on average.

Lastly, we compare our measure and the measure by Chetty et al. (2014) that is computed by exploiting the microdata of the U.S. samples. Figure E.6 shows the comparison between the model-predicted average income percentile for workers of generation 2010 and the absolute upward mobility measure in Chetty et al. (2014) across locations. Their absolute upward mobility measures the expected income rank for people born in 1980-82, which is based on income in 2011-12 relative to that of their parents in 1996-2000 and defines the expected income rank for children from families with below-median parents' income in the national distribution. We use their measures at the MSA level. In the figure, we only use the CBSAs that correspond to their metropolitan areas. As we see in this figure, the average income percentile for workers of generation 1990 is related to their measure of upward mobility. This implies that there is a correlation between the aggregate measures of the possibility of upward mobility for workers and the micro evidence across cities in the U.S, with relatively large opportunities in large cities. Figure E.7 displays a comparison of our measures of upward mobility and the absolute upward measure from Chetty et al. (2014). The correlations show that our measure of upward income mobility based on the aggregate data and model structure is related to the results based on the individual level data in the sample of Chetty et al. (2014) at the city level.

Figure E.6: Average Income Percentile of Children and Measure of Absolute Upward Mobility by Chetty et al. (2014)



Note: This figure shows the binned scatter plots for CBSAs. The horizontal axis is the measure of absolute upward mobility of the cohort 1980-82 in Chetty et al. (2014), and the vertical axis is the average income percentile of workers from the CBSA in generation 2010 computed in our calibration.

Figure E.7: Aggregate Average Upward Mobility and Measure of Absolute Upward Mobility by Chetty et al. (2014)

Note: This figure shows the binned scatter plots for CBSAs. The horizontal axis is the measure of absolute upward mobility of the cohort 1980-82 in Chetty et al. (2014), and the vertical axis is the measure of upward mobility for generation 2010 in our calibration.

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