The Geography of Structural Transformation: Effects on Inequality and Mobility

Kohei Takeda*

Department of Economics,
London School of Economics

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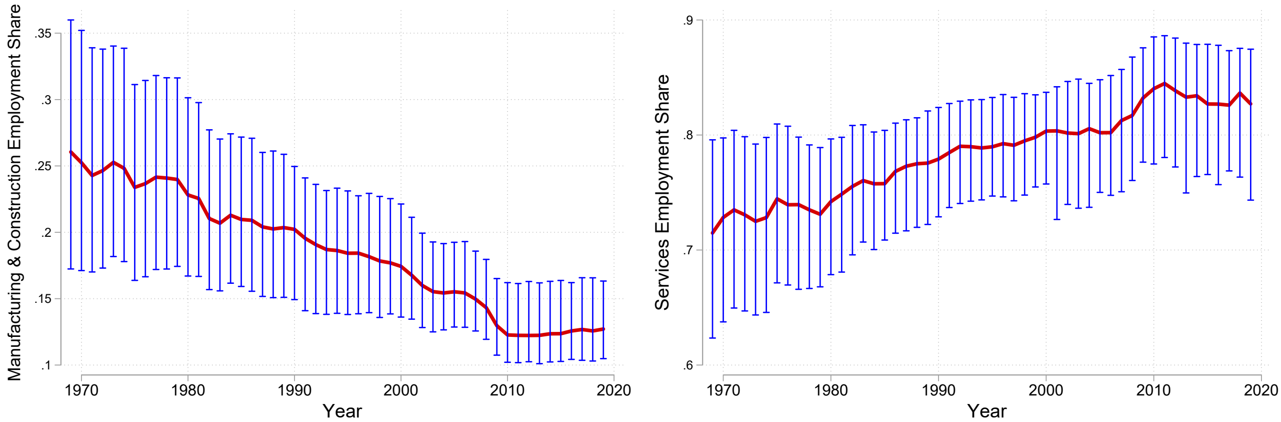
Abstract: Economies transform at an uneven pace: San Jose's meteoric rise coexists with Detroit's slow decline. This paper develops a dynamic overlapping generations model of economic geography to explain variation in structural transformation across space and time. In the model, historical exposure 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 to match metropolitan area data for 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 service sector, income mobility would be 6 percent higher, and if amenities were equalized across locations, it would rise by 10 percent.

*Department of Economics and Centre for Economic Performance, London School of Economics, Houghton Street, London WC2A 2AE, UK (e-mail: k.takeda@lse.ac.uk). I thank Oriana Bandiera, Robin Burgess, Steve Machin, Gianmarco Ottaviano and Daniel Sturm for continuous support and insightful discussions and Gabriel Ahlfeldt, Swati Dhingra, Nobuhiro Kiyotaki, Dennis Novy, Veronica Rappoport, Thomas Sampson, Catherine Thomas, Tony Venables, Atsushi Yamagishi and seminar participants for their feedback. For the most recent version of Online Appendix associated with the paper, please go to the following link here.

I 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. Figure 1 shows the change in employment shares for both the manufacturing and service sectors in US cities over the last half-century. In the left-hand panel, both the median share of people employed in the manufacturing sector and its spatial variation represented by the blue inter-quartile bands have been declining in most cities since the 1970s. In the right-hand panel, there has been concurrent growth in the share employed in the service sector. However, in contrast to the manufacturing sector, this continues to show large geographic variation. While the causes and consequences of structural transformation have been well documented at a national level, we know very little about what drives its variation across space within countries. And, importantly, the uneven impact of this structural transformation could explain both spatial inequality and geographical variation in the social mobility of workers.

Figure 1: Change in Employment Share across U.S. Cities (MSAs)



(a) Manufacturing and Construction

(b) Services

Note: These figures show the change in employment share for the manufacturing and construction sector and the service sector. The red line shows the median across MSAs in the U.S. and the blue lines show inter-quartile ranges for any particular year.

In this paper, I (i) show how amenities and productivity spillovers are the main drivers of the geographical unevenness of structural transformation and (ii) use the model and fitted data to perform counterfactuals that allow me to trace out the consequences of this variation for inequality and mobility across metropolitan areas in the US. To this end, I build a dynamic economic geography model based on a standard gravity framework 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 is caused by both differential technological progress between industries and non-homothetic demand. My model therefore 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. I then calibrate this model using data on 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.

My dynamic economic geography model 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 preferences 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. I embed this mechanism of structural transformation in the multi-sector version of the gravity model and this enables me to consider the microstructure of spatial linkages in production and consumption. Compared to the standard formula in this class of the model (Arkolakis et al. 2012), my model adds endogenous productivity spillovers through both the labor mobility and consumption margins due to non-homothetic demand. Firms are competitive and firms in each location benefit from other locations over time because they can exploit technology developed in other places through the in-migration of workers who bring knowledge with them. 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 I have defined the structure of demand, production and trade, I 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, I 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 dependency 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.

Together with these key mechanisms which drive the geographical pattern of structural change, I also provide a quantitatively oriented theory to study the consequences of the distributional effects of structural change on workers' inequality over space and time. The model allows me to characterize the local labor market dynamics with the Stolper-Samuelson effect and the Rybczynski theorem at work in the spatial economy.

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, my model with overlapping generations and workers' mobility 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 key qualitative and quantitative insights in the theoretical model, I calibrate the model with the data from U.S. metropolitan areas and multiple industries. I consider 395 core based statistical areas (CBSAs) and 17 industries in the manufacturing sector and the services sector, and a construction sector. I first estimate some parameters by exploiting the structural equations in the model. I use gravity equations for internal trade and migration to estimate their elasticities. I 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, I invert the model to recover the time-varying fundamental productivity and amenity estimates by industry and CBSAs for different periods, 1980, 1990, 2000 and 2010. While I allow for high dimensions in locations, industries and time, I find that my model remains tractable and allows me to compute these fundamentals in the real economy. Based on the inverted fundamentals and computed workers' choice, I 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.

Armed with the estimated parameters and inverted fundamentals in the economy, I perform two sets of counterfactual exercises varying (i) technological progress and (ii) local amenities. For the former, I start by quantifying the effect of fundamental technological progress on the geographical pattern of structural transformation, welfare and upward mobility. To do this I conduct a counterfactual exercise where the evolution of fundamental productivity in the service sector shows different patterns to the baseline. I also look at what happens if information technology (IT) intensive services had not experienced technological advancement over time. Namely, I compute the counterfactual equilibrium when the fundamental productivity of communication services and finance, insurance and real estate (FIRE) was fixed after a negative shock to the baseline economy in 1990. In addition, I look at a counterfactual to assess the role of technological progress in the manufacturing sector due to the adoption of robots. I 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 I find pronounced geographical variation in this effect. For the latter I perform a set of counterfactuals where I 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. To assess the importance of labor mobility, I first suppose that migration barriers are low. Further, I 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. In these model counterfactuals, I find 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. I also find that lower migration barriers yield higher geographical and income mobility for workers.

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. It is applicable to a whole range of settings beyond that examined in this paper. My key finding is that interplay between structural transformation in the aggregate and local economies is critical for understanding spatial inequality and worker mobility. The dynamic nature of my spatial model allows me 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. My paper addresses 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 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. My paper contributes by opening the black box of how the structure of economy can influence patterns of inequality and mobility in different locations.

Related Literature. My work is related to the explanation of the structural transformation in macroeconomy (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. 2020) and the neoclassical analysis of regional disparity (Barro et al. 1991, Barro and Sala-I-Martin 1992). Bairoch (1991) described the role of cities during the time of structural transformation in the world. In the context of the spatial economy, there is a line of discussions about the underlying sources of the diversity of spatial development: input-output linkages (Puga and Venables 1996), innovation and entrepreneurship (Brezis and Krugman 1997, Duranton and Puga 2001, Glaeser et al. 2015), trade costs (Redding and Venables 2004, Redding and Sturm 2008), the interregional transport network (Duranton and Turner 2012, Allen and Arkolakis 2014), spatial spillover of technology (Desmet and Rossi-Hansberg 2009, Desmet and Rossi-Hansberg 2014), and amenities (Rappaport 2007, Glaeser et al. 2016).[1] My model integrates them to make these ideas quantitatively precise, and I propose the structural approach relating to the recent empirical findings of Hornbeck and Moretti (2020).

Theory adopts the recent modeling of non-homothetic preferences to consider the role of heterogeneous Engel curves across local labor markets in the spatial pattern of structural transformation and inequality. Matsuyama (2019) studied the implication of the non-homothetic demand system in the two-country international trade model. Comin et al. (2020) investigated the non-homothetic constant elasticity of substitution (CES) demand system in the structural transformation of the macroeconomy. I adopt the non-homothetic CES demand system for keeping the tractability of the model compared to previous works using different types of preferences.[2] The modeling approach of dynamics is similar to that of Allen and Donaldson (2019). However, my study has different motivations. The extension of their framework to multiple sectors and the introduction of linkages between generations in labor supply add new insights for spatial inequality and worker mobility. The counterfactual analysis to study the quantitative importance of different margins is also related to Caliendo et al. (2018) for sectoral linkages and Hsieh et al. (2019) for labor misallocation.

The quantitative framework shares some common features with the growing literature on quantifiable general equilibrium with space (Redding and Rossi-Hansberg 2017). In particular, my research is closely related to the dynamics of the spatial economy through labor mobility and productivity spillovers. There is a list of papers that analyze the theory of dynamic equilibrium in economic geography (Krugman 1991,

[1] Others include: Banerjee and Duflo (2005) for the distortion of resource allocation across space; Rossi-Hansberg and Wright (2007) for the human capital accumulation; and Saiz (2010), Hsieh and Moretti (2019) for differences in housing supply.

[2] There are different specifications for the nonhomothetic preferences applied in international trade and urban economics: Fieler (2011), Caron et al. (2014), Simonovska (2015), Handbury (2019).

Matsuyama 1991, Ottaviano 1999, Baldwin 2001). At the expense of forward-looking choices, my approach provides tractability to isolate the importance of migration barriers, local labor market exposure, structural transformation and externalities in the workers' response to any particular shock. This is also my attitude toward the recent advancement in the formulation of the spatial dynamics of perfect foresight infinitely lived workers response to external shocks (Artuç et al. 2010, Dix-Carneiro 2014, Dix-Carneiro and Kovak 2017, Caliendo et al. 2018, Caliendo et al. 2019, Caliendo and Parro 2021, Kleinman et al. 2021). For labor mobility, my approach is also related to Porcher (2020) on the role of information friction in internal migration, although I underscore the past industry distribution in the decision to work within the local labor market. Regarding productivity spillovers, Desmet and Rossi-Hansberg (2014) and Desmet et al. (2018) built the model for technology diffusion. The model in this paper incorporates their concept but is more tractable to accommodate dynamic gain and loss from agglomeration economies, spatial linkages and consumption-led growth. This allows for a detailed description of welfare, TFP, and wealth over time and space for a wide range of shocks. Among others, Michaels et al. (2012) provided the static model that studies the link between urbanization and the shift of labor from agriculture to manufacturing. Eckert and Peters (2018) considered the dynamic version of the structural transformation of the early U.S. economy. Fan et al. (2021) accounts the regional difference in the service led growth in India. Compared to them, I explicitly consider the role of spatial linkages and frictions that are abstract in their model. The spatial structure is important. With trade costs, remote places exhibit higher prices in tradable goods. The complementarity between goods and services leads to smaller expenditure share and employment share of consumer services in the remote places even if they are endowed with high productivity. Therefore, the ordered spatial structure matters to assess the fundamental productivity. In addition, the model presents new approaches for analyzing labor mobility across locations related to the policy discussion[3].

Finally, as an essential contribution, I take an approach focused on the structural mechanisms for the recent discussion on the dynamics of inequality by geography. In addition to the cross-sectional inequality across locations (Glaeser et al. 2009, Behrens et al. 2014), I derive an implication for the heterogeneity in intergenerational mobility found in recent studies, 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's approach and quantitative results complement their evidence, and I can obtain the absolute effects of structural change in the economy on the upward income mobility of individual workers.

The rest of this paper is structured as follows. Section II describes the spatial variation of structural changes and its relation to factor prices and the upward mobility in the U.S. Section III develops the model, and Section IV describes the analytical results for accounting objectives in the model along with the numerical illustration of equilibrium. The data and parameters for calibration and calibration procedure are described in Section V. The results of calibration and quantitative analysis for the U.S. economy are discussed in Section VI. Armed with the data and parameters, Section VII presents the results of the counterfactual analysis in the U.S. economy. Section VIII concludes.

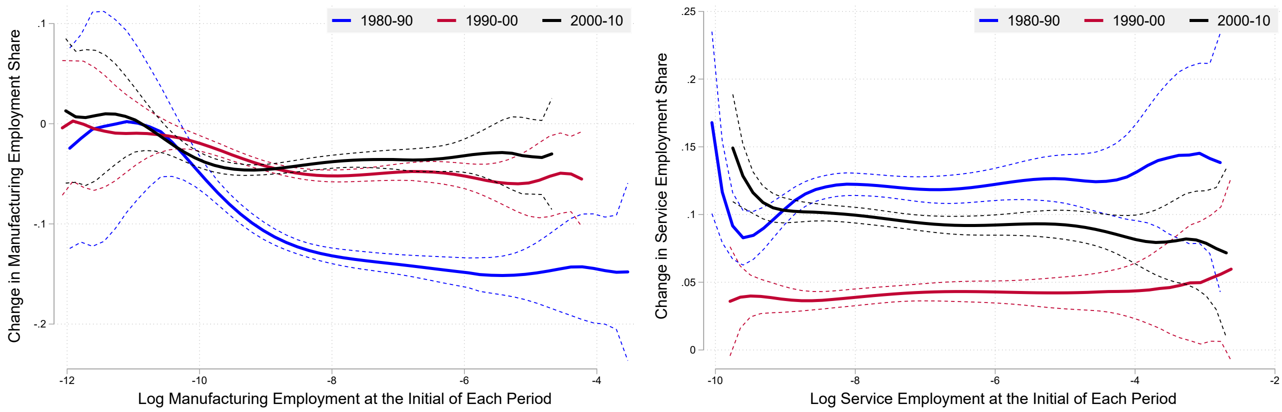
II Spatial Variation of Structural Transformation in the U.S.

I start by documenting the spatial variation of structural transformation in the U.S. economy. Figure 2 displays 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 industry level employment

[3] This includes: Diamond (2016), Giannone (2017), Fajgelbaum et al. (2019), Ossa (2019), Burstein et al. (2020)

from the county business pattern (CBP). In the left-hand panel, cities with large initial employment in the manufacturing sector showed a significant shift of workers to the services sector during $1980 - 1990$. Although this pattern became less pronounced in the later periods, it shows that the deindustrialization of the U.S. economy has been led by cities where the size of the manufacturing sector was large. This implies that employment in the manufacturing sector has been dispersed across space over time. In the right-hand panel, the service sector exhibited a weak relationship between the change in the employment share of the services sector and the initial size of employment in the sector. This shows that the variation in the employment share of services across cities has not declined over time in contrast to the manufacturing sector. Another observation in these figures is a large variation in the change of employment composition for specialized cities. For both the manufacturing sector and service sector, the confidence intervals become large for cities with large size of employment in a particular sector. One logic that creates the spatial variation in this structural transformation is the differential productivity growth across space through fundamental technological differences and productivity spillovers across space. Therefore, my model allows spatial heterogeneity in fundamental productivity growth and spillovers. Another driver of this geographical unevenness in structural transformation is a significant difference in demand. In the U.S., while the average expenditure share of goods has declined and that for housing and services has increased in most places, there is considerable variation in expenditure share across cities. In addition, a larger expenditure share on services is associated with a large consumption expenditure and the relationship has been observed for different periods. See Online Appendix for the expenditure share for some representative cities in the U.S. To reconcile this pattern, I incorporate the non-homothetic preferences of individuals in the model. This leads to the different slope of the Engel curve of workers by their locations and industries.

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

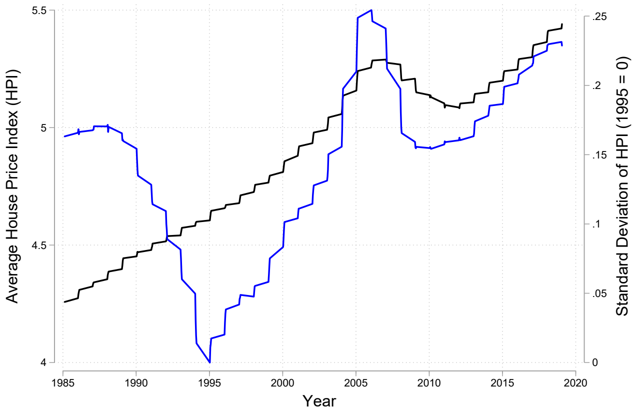


(a) Manufacturing (b) Services

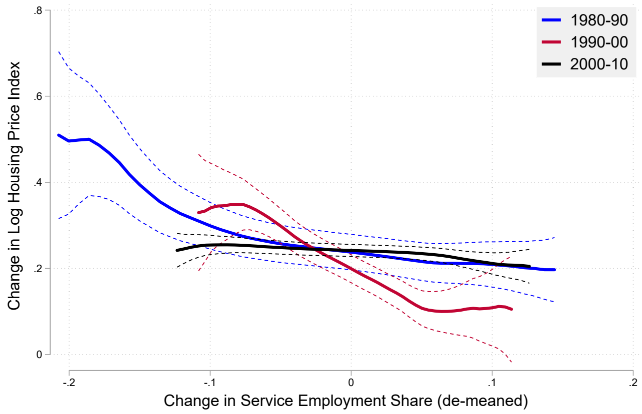
Note: These figures show the polynomial fitted line (polynomial of degree six) for the change in employment share between different periods: $1980 - 1990$, $1990 - 2000$ and $2000 - 2010$. Figure (a) shows that for the manufacturing sector, and Figure (b) shows that for the service sector. The sample includes 395 core based statistical areas (CBSAs) in the U.S. The dotted lines show 95% confidence intervals. Employment is normalized by the total employment in the economy.

The population distribution is uneven across cities and agglomerations change the value of local amenities, which is reflected in land and housing prices. Figure 3 shows the changes in the U.S. economy in the average and standard deviation of the house price index and its relation to the structural change. In the left-hand panel 3a, the standard deviation decreased before 2000, then increased. The right-hand panel 3b confirms that changes in housing prices are relatively small in markets where services are concentrated, and the initial housing prices are high in the $1990 - 2000$ period. This is consistent with the decline in the variation of housing prices. In contrast, there has been a polarization in housing prices since 2000. These variations in the housing prices and the underlying local amenities are essential margins that account for the welfare disparity by place occurring in the structural transformation phase. In the model, I introduce the different

Figure 3: Spatial Variation of Housing Prices in the U.S.



(a) Variation of House Price Index



(b) Housing Price and Employment Change

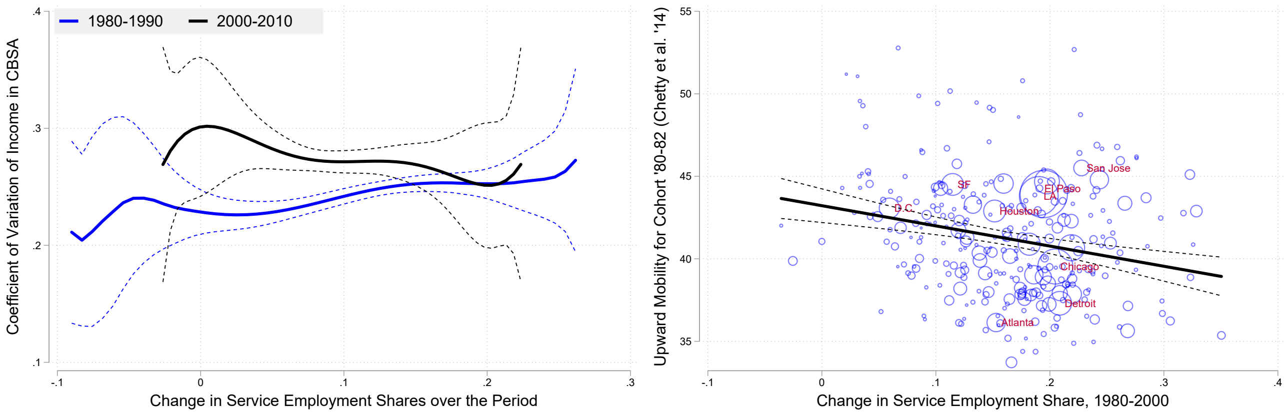
Note: Panel (a) shows the change in the average house price index (HPI) and the standard deviation of HPI across MSAs. The black line (corresponding to the left axis) is the average HPI, and the blue line (corresponding to the right axis) is the standard deviation of HPI across MSAs. HPI is normalized to the first quarter of 1995; therefore, the standard deviation of HPI in the quarter is zero. Panel (b) shows the relationship between the change in the log of HPI and the change in the service employment share. Different lines show the polynomial fitted line across MSAs, and the dotted lines are 95% confidence intervals. The change in employment share is de-meaned. The data source for HPI is Federal Housing Finance Agency (FHFA).

value of amenities for workers by location and sector and developers that supply residential stocks. I discuss the variation of the price of residential stocks across space and time and how it is related to the pattern of structural transformation.

Lastly, Figure 4 shows the relationship between inequality in the local labor markets (CBSAs) and the change in service employment share. This is consistent with the significant income inequality in large cities where employment of services increased in $1980-1990$ but turned out less pronounced later. Turning to intergenerational mobility, Figure 4b displays the variation in the measure of upward mobility of workers across metropolitan areas constructed by Chetty et al. (2014) and its relation to the change in the service employment share. The measure of upward mobility represents the expected rank for children from families with below-median parents' income in the national distribution. They exploit residents born in $1980-82$ and their income is evaluated in the years $2011-12$, and related to the income of their parents back in $1996-2000$. There is a large variation across U.S. cities in the upward mobility, and the structural transformation toward the service sector in the local labor market is associated with lower intergenerational income mobility for workers. In the next section, I develop a quantifiable model to consider the variation of upward mobility and its relation to structural transformation. Intuitively, more structural transformation to services inherently low productivity growth in the local economy and the lower degree of labor mobility together lead to lower upward mobility. Therefore, the current labor composition of the local economy and the pattern of structural transformation is important to create the variation of upward income mobility. Modeling with overlapping generations and workers' mobility 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.

The heterogeneity in structural transformation across space gives rise to the question of its redistributive effects across space and over generations. What are the underlying drivers that create the spatial variation of structural transformation? What is their quantitative importance in explaining the spatial inequality and upward mobility of workers in the U.S. economy? To address these questions, I build the quantifiable general equilibrium model that accommodates heterogeneous geography, fictional adjustment of workers across

Figure 4: Inequality and Intergenerational Mobility across the U.S. Cities



(a) Urban Inequality (b) Upward Income Mobility

Note: (a) Inequality within local labor market is measured by the coefficient of variation (CV) of income. The polynomial fitted line for CBSAs in the U.S. Dotted lines show 95% confidence intervals. (b) 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.

locations and industries, and structural transformation.

III The Model

I develop a theoretical framework that investigates the spatial heterogeneity of structural transformation and its consequence of inequality in the dynamic spatial economy. The mechanisms behind the structural transformation are together demand driven consumption inequality and heterogeneous distribution of industries founded by the trade costs and agglomeration economies. Those mechanisms highlight how shocks in the economy lead to changes of labor mobility and industrialization across geography. Those dynamics, in turn, creates the dynamics of both nominal and real income inequality along with the spatially biased regional industry reallocations.

The basic environment is following. Time is discrete. A single country consists of a discrete number of locations, indexed by i, ℓ or $n \in \mathcal{N}$. I let $\mathcal{K}$ denote the set of $S+1$ industries: there are S tradable industries and single sector providing the structure or housing services, which I refer sector 0. Each sector is indexed by j, k or s. Locations are different in fundamental productivity, amenity and land endowment. Immobile landlords own the raw land, and the total units of land is T_i, and it is unchanged over time. Locations differ in terms of fundamental amenity $\mathbf{B}_t = \{B^s_{i,t}\}$ and fundamental productivity $\mathbf{A}_t = \{A^s_{i,t}\}$. 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. Each local labor market is characterized by the combination of location (i) and industry (s). 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 *formative years*. Online Appendix A presents the details of each element in the model not included in the main text.

III.A Demand, Land of Opportunity, and Exposure in Local Labor Market

I consider the individuals' decisions for the consumption, industry to work and location. At the initial of time $t-1$, people of generation t are homogeneous ex ante.[4] During the period $t-1$, individuals in location i observe the idiosyncratic taste shocks relating to the industry choice for future. They anticipate the wage and prices in the next period t and compute expected payoff for the future. Given the expected payoff, they decide the industry, and I take that choice is unchanged later. At the initial of period t, individuals draw and observe the amenity 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 s in period t is:

$$\ln U^s_{ni,t}(\omega) = \ln B^s_{n,t} + \ln \mathbb{C}^s_{n,t}(\omega) - \ln D_{ni,t} + \ln z^s_{i,t}(\omega) + \ln v_{n,t}(\omega),$$

where $\mathbb{C}^s_{n,t}(\omega)$ is *subutility* function associated with consumption of individuals. The utility benefit from amenity, $B^s_{n,t}$, is common to sector s workers living in n, and migration from location i to n incurs the utility cost $D_{ni,t}$ that reflects any impediments that movers across locations face.[5] The idiosyncratic taste shocks from industry choice $z^s_{i,t}(\omega)$ depends on the origin of the worker. The second idiosyncratic shocks of amenity, $v_{n,t}(\omega)$, depends on the destination but independent across i and s. I describe them in detail later.

For the demand system, my objective is to study the implication of demand heterogeneity across workers and locations along with the structural transformation in the economy. Therefore, I depart from the standard CES demand by introducing a heterogeneous income effect across sectors, keeping tractability in the substitution effect. To this end, in the baseline analysis, I adopt the implicitly additive separable consumption aggregator featuring non-homothetic CES demand discussed in Hanoch (1975) and recently Matsuyama (2019) and Comin et al. (2020). While there are alternative approaches In the international trade and macroeconomics literature[6], as I discuss below, the non-homothetic CES demand system in the baseline analysis has advantages: first, I keep non-homotheticity in the asymptotic; second, I easily accommodate multi-sectors; third, the elasticity of substitution between sectors is constant; and fourth, the elasticity of relative sectoral demand with respect to aggregate demand is solely determined by parameter values. These gain tractability and entail the core mechanisms of demand shift.

Workers of generation t working in location n and sector s receives income $W^s_{n,t}$ which include labor earnings (wage) and surplus distributed among workers. I refer $\boldsymbol{p}_t = \{p^k_{n,t}\}$ to price of consumption of goods. The expenditure share of a worker with income $W^s_{n,t}$ is given by:

$$\psi^s_{k|n,t} = \alpha_k^{\sigma-1}\left(p^k_{n,t}/\mathcal{P}^s_{n,t}\right)^{1-\sigma}\left(W^s_{n,t}/\mathcal{P}^s_{n,t}\right)^{\theta_k-1}, \quad k \in \mathcal{K} \tag{1}$$

where $\boldsymbol{\alpha} = \{\alpha_k\}$, σ and $\boldsymbol{\theta} = \{\theta_k\}$ are exogenous preference parameters and I assume $(\theta_k - \sigma)/(1-\sigma) > 0$ for all industries.[7] $\mathcal{P}^s_{n,t}$ is aggregate ideal price index corresponding to the optimal consumption patterns for

[4] This can be easily extended to allow exogenous heterogeneity including race and gender. See discussion in the subsection III.E.

[5] This conceptually includes moving costs between locations, the cost of job search in different locations, as well as the cost of searching a place to live. For any location i, I assume that $D_{ii,t} = 1$ when I discuss the analytical results. This assumes that people can relocate within the same location between two periods at the same cost across locations. Yet, in the quantification of the model, I allow $D_{ii,t}$ may different across locations.

[6] The different types of non-homothetic preferences include: Stone-Geary preference; price independent generalized linearity (PIGL) preference (Buera and Kaboski 2012, Eckert and Peters 2018); constant ratio of income elasticity (Fieler 2011, Caron et al. 2014); income specific elasticity of substitution between goods (Handbury 2019).

[7] This ensures the global monotonicity and quasi-concavity of the consumption aggregation. See Online Appendix A.1 for details.

workers in sector s and location n that solves:

$$\mathcal{P}_{n,t}^{s}=\left(\sum_{k\in\mathcal{K}}\alpha_{k}^{\sigma-1}(p_{n,t}^{k})^{1-\sigma}(W_{n,t}^{s}/\mathcal{P}_{n,t}^{s})^{\theta_k-1}\right)^{1/(1-\sigma)} \tag{2}$$

Using the price index, I let $\mathcal{W}_{n,t}^{s}$ denote the real income for workers in location n and sector s: $\mathcal{W}_{n,t}^{s}\equiv W_{n,t}^{s}/\mathcal{P}_{n,t}^{s}$. If $\theta_k=1$ for all k, this becomes standard (homothetic) CES price index. I emphasize the three key elasticities for this demand system (1). First, the elasticity of substitution between sectors is $1-\sigma$ which keeps the feature of the standard CES demand function. Second, the elasticity of *relative* demand between two different sectors to the *aggregate demand* is specific to the pair of sectors and the elasticity is governed by θ_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 large θ_k. When expenditure shifts to an industry with large θ_k, the income elasticity of consumption becomes lower as the relative slopes of Engel declines for all sectors.

I let $Y_{n,t}^{s}\equiv W_{n,t}^{s}L_{n,t}^{s}$ be aggregate income of workers in location n and sector s and $Y_{n,t}\equiv\sum_{s\in\mathcal{K}}Y_{n,t}^{s}$. I also define income share of workers in any particular industry: $y_{n,t}^{s}\equiv Y_{n,t}^{s}/Y_{n,t}$. Then, the change of local expenditure share on sector k between time t and $t-1$ at the first order approximation becomes:

$$\mathrm{d}\ln\frac{E_{n,t}^{k}}{Y_{n,t}}=\sum_{s\in\mathcal{K}}\frac{\psi_{k|n,t-1}^{s}Y_{n,t-1}^{s}}{E_{n,t-1}^{k}}\left[(1-\sigma)\mathrm{d}\ln\left(\frac{p_{n,t}^{k}}{\mathcal{P}_{n,t}^{s}}\right)+(\theta_k-1)\mathrm{d}\ln\mathcal{W}_{n,t}^{s}+\mathrm{d}\ln y_{n,t}^{s}\right] \tag{3}$$

where $E_{n,t}^{k}$ is aggregate expenditure on sector k in location n. The local level Engel slope changes over time through substitution effect, real income change ($\mathcal{W}_{n,t}^{s}$) and the change of income distribution ($y_{n,t}^{s}$) given previous expenditure patterns.

Turning to the location choice of workers, I formally posit the followings for the stochastic factor:

ASSUMPTION 1 *An individual draws vector $\boldsymbol{v}=\{v_{i,t}(\omega)\}_{i\in\mathcal{N}}$ from the time invariant multivariate distribution: $G(\{v_{i,t}(\omega)\})=\exp\left(-\sum_{i\in\mathcal{N}}(v_{i,t})^{-\epsilon}\right)$. $v_{i,t}(\omega)$ and $v_{n,t}(\omega)$ are independent: $v_{i,t}(\omega)\perp v_{n,t}(\omega)$ for any $i\neq n$ conditional on industry choice.*

The shape parameter reflects the dispersion of the idiosyncratic utility. Low ϵ implies higher heterogeneity in taste across places to live, and $\epsilon\to\infty$ implies that all individuals face the same order of locations in terms of the utility benefit. Under Assumption 1, the probability that worker born in i at period $t-1$ ends up working in location n at period t conditional on choosing industry s equals:

$$\lambda_{ni|s,t}=\left(\frac{B_{n,t}^{s}\mathcal{W}_{n,t}^{s}}{D_{ni,t}\bar{U}_{i,t}^{s}}\right)^{\epsilon}\quad\text{with}\quad\bar{U}_{i,t}^{s}=\left(\sum_{\ell\in\mathcal{N}}\left(B_{\ell}\mathcal{W}_{\ell,t}^{s}/D_{\ell i,t}\right)^{\epsilon}\right)^{1/\epsilon} \tag{4}$$

$\bar{U}_{i,t}^{s}$ is expected utility conditional on job choice s. By law of large numbers across continuum of individuals, each element of matrix $\boldsymbol{\lambda}_{s,t}=\{\lambda_{ni|s,t}\}$ characterizes the share of movers among individuals of generation t conditional on industry choice s. The share becomes large when the destination exhibits higher real income from consumption ($\mathcal{W}_{n,t}^{s}$) associated with the adjustment of amenity value ($B_{n,t}^{s}$) and discount of migration costs ($D_{ni,t}$). Therefore, $\bar{U}_{i,t}^{s}$ reflects the land of job opportunity for individuals born in i when working in industry s.

I turn to the distribution of idiosyncratic taste shocks relating to the choice of industry, $\boldsymbol{z}_t=\left\{z_{i,t}^{s}(\omega)\right\}$. An individual of generation $t+1$ in location i receives the discrete number of taste shocks for each sector from previous generation t during the formative period, t. An individual of generation $t+1$ (*young*) spends entire one unit of time for job choice during period t. An individual acquires information containing taste shock from existing workers in the local labor market. An individual split one unit time into T time spans with interval Δ, and she receives the valuable information regarding industry s with probability $J^s_{i,t}$ during Δ. Within each time span, an individual decides time allocation across different industries to maximize the logit of probabilities of receiving the valuable shocks. I let $\mathcal{O}(J^s_{i,t}, L^s_{i,t})$ denote time required to achieve the probability $J^s_{i,t}$. This is increasing in $J^s_{i,t}$ and decreasing in $L^s_{i,t}$. Intuitively, 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 average of odds that captures the chance of receiving valuable taste shocks relative to valueless ones regarding industries with minimizing the average coefficient of variation for the number of valuable taste shocks in a unit time.[8] Specifically, during time span Δ, an individual of generation $t+1$ in location i solves:

$$J^s_{i,t} = \arg\max_{j^s_i \in (0,1)} \left\{ \sum_{k\in\mathcal{K}} \ln \frac{j^k_i}{1-j^k_i} \quad \text{s.t.} \quad \sum_{k\in\mathcal{K}} \mathcal{O}(j^k_i, L^k_{i,t}) \leq \Delta,\ \mathcal{O}(j^k_i, L^k_{i,t}) \equiv \frac{1}{\zeta_{k,t}} \ln\left(\frac{1}{1-j^k_i}\right)(L^k_{i,t})^{-\eta} \right\} \tag{5}$$

The first constraint is time constraint. In the specification for $\mathcal{O}(J^s_{i,t}, L^s_{i,t})$, $\zeta_{s,t}$ and η are strictly positive constant. $\zeta_{s,t}$ 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 that the number of shocks an individual of generation $t+1$ receives during a unit of time is following Poisson distribution with arrival rate $J^s_{i,t}$. Further, to gain the tractability, the value of each shock is supposed to be following Pareto distribution with shape parameter ϕ and shocks are independent. The parameter ϕ defines tail of Pareto distribution and small value implies fat tail distribution for the size of shocks. Intuitively, if ϕ becomes small, an individual is more likely to receive higher value of shock in job choice. Therefore, there is 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 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 $\phi > 1$.*

Intuitively, this assumption argues that individuals face the *consideration set* when deciding future industry and location of work, and the set is influenced by the labor market environment. Given the set, individuals make their decisions following subjective expectations about future returns.[9] Let $m^s_{i,t}(\omega)$ be the number of shocks an individual receives from location i and industry s. An individual decides industry s to work in if and only if:

$$s \in \left\{ k \ :\ \max_{m\in\{1,2,\cdots,m^k_{i,t}(\omega)\}} \bar{U}^k_{i,t} {z^k_{i,t}}^{(m)} \geq \max_{s'\in\mathcal{K}} \max_{m\in\{1,2,\cdots,m^{s'}_{i,t}\}} \bar{U}^{s'}_{i,t} {z^{s'}_{i,t}}^{(m)} \right\}. \tag{6}$$

Under Assumption 2, I derive the share of cohorts $t+1$ in location i that choose industry s:

$$\varsigma^s_{i,t+1} = \zeta_{s,t}(L^s_{i,t})^\eta \left(\frac{\bar{U}^s_{i,t+1}}{V_{i,t+1}}\right)^\phi \quad \text{with} \quad V_{i,t+1} \equiv \left(\sum_{k\in\mathcal{K}} \zeta_{k,t}\left(L^k_{i,t}\right)^\eta \left(\bar{U}^k_{i,t+1}\right)^\phi\right)^{1/\phi}. \tag{7}$$

[8] The coefficient of variation captures the relative variation of number of valuable information over the average number of valuable information. Minimizing such variation is isomorphic to maximizing the logit.

[9] The subjective expectation about future wage differentials is an important factor that affects young people's schooling and career choices (Dominitz and Manski 1996, Keane and Wolpin 1997).

The matrix $\varsigma_t = \{\varsigma^s_{i,t}\}$ close the individuals' decision process and it determines the geographical distribution and its dynamics of labor supply. The share of individuals, $\varsigma^s_{i,t+1}$, depends on three components. The shifter $\zeta_{s,t}$ translates the macro effect in the industry choice that is common across locations. The large probability of choosing sector s is associated with large size of employment in previous generation ($L^s_{i,t}$). Intuitively, more existing workers in the local labor market can save the marginal cost of information acquisition and it turns to be large number of expected number of shocks that arrive to young generation *ceteris paribus*. This result can be interpreted as a path dependency in job choices at the local labor market over generations.

This formulation under Assumption 2 is consistent with empirical evidences of intergenerational linkage in job choices and work behavior in labor economics[10]. In particular, the path dependency in the specification may capture the path dependency in the local labor market through education. Some U.S. manufacturing cities, including Buffalo, Cincinnati and Youngstown (Ohio), have underdeveloped the infrastructure to educate young generations for a long time, and the number of high school and college graduates has been low in these cities. For these cities, the industrial specialization leads to the 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. Therefore, specialization of the industry has a long-term effect over generations through the accumulation of schooling.[11] The specification of workers' idiosyncratic taste shocks also reflects the recent literature in the intergenerational transmission of preference apart from the endogenous creation of human capital or productivity. In their findings, the previous generation affects the formation of preference and risk attitude for the current generation through the neighborhood effects and the formal or informal social interactions. [12] Lastly, individuals of cohort $t+1$ choose sector s with high probability when conditional expected utility ($\bar{U}^s_{i,t}$) is large since it determines the advantage of industry s in terms of net gain for their future.

III.B Technology and Trade

I build on the multi-sector and multi-location Ricardian model embedded with input-output linkages and externalities from agglomeration. In each tradable sector, there are final good producers and intermediate good producers. In each location, final good producers supply local consumption goods and materials using sector-specific intermediate goods, and their technology is CES with elasticity of substitution $\tilde{\kappa}$. The final goods producers supply consumption goods or materials in a competitive fashion but they are consumed locally. The time span of each period is not too short, and I assume that final goods are produced and used as

[10] 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. Kramarz and Skans (2014) investigated the relationship between parental network and job entry of their children. They 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 the direct evidence on intergenerational transmission of employers in Canada; Lindquist et al. (2015) found that the probability of children's entrepreneurship increases by around 60 percent given parental entrepreneurship in Sweden. 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).

[11] To consider the movement of people for education, I extend the baseline model to include the additional choice of individuals for education. See subsection III.E for further discussion.

[12] The relationship between generations in the job choice can be explained by the (unobserved) transmission of taste or preference instead of investment of education or financial assets. For example, in the historical context, Doepke and Zilibotti (2008) highlighted the impact of the previous economic environment on the formation of the preference among the future generation. Dohmen et al. (2012) found that the risk attitudes in preference are transmitted from parents to children and there is a neighborhood effect in the transmission. Fernández et al. (2004) and Fernandez and Fogli (2009) suggested that there are significant effects of female labor participation in the previous generation on the work and fertility behavior among the second generation, and this reflect the persistence of the formation of preference between generations. These pieces of evidence suggest that the non-cognitive transmission of taste over generations matters to explain the observed behaviors of agents, and the transmission occurs in the formal or informal social interactions discussed in Manski (2000).

inputs simultaneously in each period. Therefore I do not consider the dynamic decision among firms.

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 $\boldsymbol{Z} = \{Z_{i,t}^s\}$ and firm specific productivity that is drawn from Fréchet distribution with shape parameter $\kappa_s > 1$ in the wake of Eaton and Kortum (2002). Intermediate goods can be traded incurring a sector-specific iceberg trade cost, so that delivering one unit of an intermediate good from n to i requires $\tau_{in,t}^s \geq 1$ units, with $\tau_{ii,t}^s = 1$. The probability that final producers of sector s in location i source intermediate goods from location n is:

$$\pi_{in,t}^s = \frac{(\tau_{in,t}^s \Xi_{n,t}^s / Z_{n,t}^s)^{-\kappa_s}}{\sum_{\ell \in \mathcal{N}} (\tau_{i\ell,t}^s \Xi_{\ell,t}^s / Z_{\ell,t}^s)^{-\kappa_s}} \quad \text{with} \quad \Xi_{n,t}^s = (w_{n,t}^s)^{\beta_s} \prod_{j \in \mathcal{K} \setminus 0} (p_{n,t}^j)^{\beta_{sj}} \tag{8}$$

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

$$p_{i,t}^s = \Gamma_s \left(\sum_{\ell \in \mathcal{N}} \left(\tau_{i\ell,t}^s \Xi_{\ell,t}^s / Z_{\ell,t}^s \right)^{-\kappa_s} \right)^{-1/\kappa_s} \tag{9}$$

where $\Gamma_s \equiv \Gamma\left(1 - \frac{\tilde{\kappa}-1}{\kappa_s}\right)^{1/(1-\tilde{\kappa})}$ is constant. The trade elasticity for industry s is κ_s. The gravity structure of regional trade characterized by (8) and (9) 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. I make the following assumption:

ASSUMPTION 3

$$Z_{i,t}^s = A_{i,t}^s \left(\sum_{n \in \mathcal{N}} L_{in,t}^s Z_{n,t-1}^s \right)^{\rho} \left(L_{i,t}^s \right)^{\gamma_s}$$

for all $i \in \mathcal{N}$ and $s \in \mathcal{K} \setminus 0$.

I allow the fundamental productivity $A_{i,t}^s$ to change over time to reflect the technology change in sector s in the local economy. Suppose that $\rho = 0$. Then, productivity increases in the size of local workers to power $\gamma_s > 0$, which naturally arises when economies of scale exist. Suppose that $\rho > 0$. Each location benefits from other locations through workers (including stayers) who have ideas of sector s. Then, the formulation of productivity spillover in Assumption 3 captures has two features. First, the "technology" is embodied with workers in tacit form (Polanyi 1958), and it moves across locations over generations. 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 the previous places – standing on the shoulders of Giants.[13] Second, technology spillover across space depends on the by the local economic conditions. Intuitively, inflow of workers ($L_{in,t}$) reflects the current economic condition in location i. Therefore, gains from the productivity spillover is high in the location with high real income. This is in line with the classical study of the technology diffusion across space (Griliches 1957). Further, this representation claims that locations differ in technology adaption to the macroeconomy trend of productivity change in the exogenous term of $\mathbf{A}_t = \{A_{i,t}^s\}$. The exogenous environment may create a random difference of productivity across space, while employment growth and flow of "ideas" create the self-organizing technological advancement across space that is related to labor mobility and demand-led growth.[14]

[13] A series of works Desmet and Rossi-Hansberg (2009, 2014) and Desmet et al. (2018) introduced the explicit mechanisms of local technology diffusion and spatial correlation of productivity.

[14] When $\rho = 0$ and $\gamma_s = 1/\kappa_s$, this specification is isomorphic to the new economic geography model in which the mass of firms

III.C Development of Residential Stocks

Sector 0 denotes residential structure in each location. The structures are produced by a competitive developer sector who can convert structures over the residential land $\boldsymbol{T} = \{T_i\}$. I let $h_{i,t}$ refer to the stock of structure per unit of land in period t and ν_i refer to the constant depreciation rate. The production technology of a developer sector exhibits constant return to scale. Letting $l^0_{i,t}$ be the employment per unit of land for development sector, I specify the technology by:

$$h_{i,t} = \nu_i \left(l^0_{i,t}\right)^{\chi} \left((1-\bar{h}_i)h_{i,t-1}\right)^{1-\chi} \tag{10}$$

Therefore, I think of development as the process of adding structure to the previous stocks by exploiting labor. The productivity is unchanged over time and normalized.[15] The share of labor in construction is given by χ. I also think ν_i as a fundamental advantage of location in the supply of residential stocks and $\bar{h}_i$ captures the efficiency in the renewal of residential stocks or depreciation rate. Small value of $\bar{h}_i$ leads to relative increase of residential stocks conditional on the current stock.

I consider the bidding process for developers to obtain the right to develop the place by paying rent to landlords. I denote the bidding price by $r_{i,t}$ per unit of land. The aggregate surplus extracted from developers in location i through bidding becomes:

$$R_{i,t} = r_{i,t}T_i = (1-\chi)\nu_i p^0_{i,t} \left(L^0_{i,t}\right)^{\chi} \left((1-\bar{h}_i)H_{i,t-1}\right)^{1-\chi} \tag{11}$$

Landlords in each location collect the surplus $R_{i,t}$ and this captures classical idea of law of rent by David Ricardo: the total land rent is equal to the share of land in total cost of production. 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 development of land.

Lastly, I make an assumption about the division rule of the surplus among the population to take the general equilibrium effects into account.

ASSUMPTION 4 *In each location, individuals hold a portfolio of land that is proportional to their labor earnings share.*

On top of the tractability, Assumption 4 does not distort the income distribution at location since income is proportional to wage.[16] I refer $\widetilde{W}_{it}$ to the total labor earnings of generation t in location i and I let $\mu_{i,t} = 1 + R_{i,t}/\widetilde{W}_{i,t}$. Under Assumption 4, the income of each individual of sector s in location i becomes $W^s_{i,t} = \mu_{i,t} w^s_{i,t}$.

III.D Equilibrium and Aggregate Dynamics

I now move to the aggregation in the economy to define the equilibrium. Combining individuals' choices in self-selection ς_t in (7) and gravity structure of migration $\boldsymbol{\lambda}_t$ in (4) determine the spatial allocation of labor and

is proportional to the mass of labor due to the fixed cost of entry and monopolistic competition. Nevertheless, I emphasize the caveat in the interpretation. 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. See discussion in Online Appendix A.3.

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

[16] Another way of distribution rule is that the total land rent is divided among people with equal share. Then, the income becomes $w^s_{i,t} + R_{i,t}/L_{i,t}$. The drawback of this specification is that income ratio between workers in different sectors are not preserved. This feature is not convenient in the analysis of inequality of 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 mine they do.

its dynamics:

$$L_{i,t}^{s}=\sum_{n\in\mathcal{N}}\lambda_{ni|s,t}\varsigma_{n,t}^{s}L_{n,t-1}, \tag{12}$$

where $L_{n,t-1}$ is the total population of generation $t-1$ that choose location n: $L_{n,t-1}=\sum_{s\in\mathcal{K}}L_{n,t-1}^{s}$. In this equilibrium condition, I suppose that the ex ante indirect utility of generation t born in i is equalized: the value of the outside option for generation t born in i becomes equal to $V_{i,t}$ to preserve the total population over generation.[17]

Given the consumption pattern of workers $\boldsymbol{\psi}_t$ and trade pattern $\boldsymbol{\pi}_t$, the market clearing conditions for final goods implies that the total value of production of sector s is:

$$X_{i,t}^{s}=\sum_{j\in\mathcal{K}\setminus 0}\beta_{js}\sum_{n\in\mathcal{N}}\pi_{ni,t}^{j}X_{n,t}^{j}+\sum_{k\in\mathcal{K}}\psi_{s|i,t}^{k}W_{i,t}^{k}L_{i,t}^{k}, \tag{13}$$

where, on the right-hand-side, the first term is demand from intermediate producers in location i for use of materials, and the second term is aggregate demand from individuals consumption.[18] Analogously, the market clearing condition for residential stocks is:

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

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

$$\begin{aligned} w_{i,t}^{s}L_{i,t}^{s}&=\beta_{s}\sum_{n\in\mathcal{N}}\pi_{ni,t}^{s}X_{n,t}^{s},\\ w_{i,t}^{0}L_{i,t}^{0}&=\chi\nu_{i}p_{i,t}^{0}\left(L_{i,t}^{0}\right)^{\chi}\left((1-\bar{h}_{i})H_{i,t-1}\right)^{1-\chi}\end{aligned} \tag{15}$$

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

I define the equilibrium in the economy. I let $\boldsymbol{\mathcal{F}}_t$ denote the set of time-varying fundamentals, and $\widetilde{\boldsymbol{\mathcal{F}}}$ denote set of time-invariant fundamentals. $\boldsymbol{\mathcal{F}}_t$ includes migration costs between locations ($D_{ni,t}$), trade costs ($\tau_{in,t}^{s}$), exogenous productivity growth ($A_{i,t}^{s}$), amenities ($B_{i,t}^{s}$) and exogenous shifter of macroeconomy taste ($\zeta_{s,t}$). $\widetilde{\boldsymbol{\mathcal{F}}}$ includes efficiency in development of housing (ν_i), re-structuring parameter ($\bar{h}_i$) and endowment of land (T_i). For the initial state, $\boldsymbol{\mathcal{G}}_0$ includes the initial population distribution in the economy, the initial productivity ($Z_{i,0}^{s}$) and the initial endowment of residential structure (i.e., housing). $\boldsymbol{\Omega}$ denotes the set of parameters associated with demand system, choice of individuals, migration elasticity, production technology, trade elasticities, and productivity spillover. Then, variables of interest are dynamics of $(\boldsymbol{\psi}_t,\boldsymbol{\lambda}_t,\boldsymbol{\varsigma}_t,\boldsymbol{\pi}_t,\mathbf{p}_t,\mathbf{w}_t,\boldsymbol{H}_t,\boldsymbol{r}_t)$: expenditure patterns, location choice of workers, sector choice of workers, pattern of trade, price of consumption goods and housing, wage, amount of residential structure and land rent.

[17] I let $\mathbb{V}_{i,t}$ be the value of outside option for generation t born in location i. If $V_{i,t}<\mathbb{V}_{i,t}$, people move to outside option and total population of generation t is strictly lower than $L_{i,t-1}$. If $V_{i,t}=\mathbb{V}_{i,t}$, I suppose that people stay in the economy and total population of generation t is equal to $L_{i,t-1}$. If $V_{i,t}>\mathbb{V}_{i,t}$, potentially people in outside option enter into the economy, therefore total population of generation t is equal to or more than $L_{i,t-1}$. Hence, I suppose that $V_{i,t}=\mathbb{V}_{i,t}$ in equilibrium to equalize the total population of generation t to $L_{i,t-1}$, and $\mathbb{V}_{i,t}$ is determined endogenously.

[18] To simplify the discussion, I do not include the net export to the international market here. Yet, it is straightforward to include the exogenous term of the net export.

DEFINITION 1 *Given* $(\mathcal{F}_t,\ \widetilde{\mathcal{F}},\ \mathcal{G}_0,\ \boldsymbol{\Omega})$*, the dynamic equilibrium of the economy is characterized by endogenous sequences of:* ψ_t *solving utility maximization,* $\boldsymbol{\lambda}_t$ *determined by (4),* ς_t *determined by (7),* $\boldsymbol{\pi}_t$ *determined by (8),* $\mathbf{p}_t$ *that solve market clearing conditions (13) and (14),* $\mathbf{w}_t$ *that solves labor market clearing condition (15), and* $\boldsymbol{H}_t$ *and* $\boldsymbol{r}_t$ *solving profit maximization of developers (10) and (11).*

The dynamic equilibrium describes the full transition of economic activities over time and space. In Online Appendix B.1, I discuss the forward solution of the model. Given the pre-period state, I solve the equilibrium system to characterize the next period. To guarantee the uniqueness of the forward solutions, I need assumptions on parameters of (i) variation of idiosyncratic shocks, (ii) trade elasticity, (iii) non-homotheticity of demand system, and (iv) externalities in productivity. Intuitively, larger variation in labor mobility (ϵ and ϕ) and trade (κ_s) and difference in expenditure patterns (θ_s and σ) across workers are related to more labor mobility in the equilibrium, while lower agglomeration forces (γ_s) prevents the concentration of workers as in *black hole*. For the concrete discussion, I consider the special case in which $\rho = 0$ and $\chi = 1$. This implies that the externalities in productivity are purely local economies of scale and the supply of residential stocks is elastic. In this case, the dynamic equilibrium conditional on the initial state is unique when $\gamma_s \leq \frac{\theta_s - \sigma}{\kappa_s + (1-\sigma)}\left(1 + \frac{1}{\epsilon}\right)$. This condition is intuitive. When $\epsilon \to \infty$, the idiosyncratic shocks for migration are homogeneous across workers, and it requires a small value of γ_s to avoid generating multiple equilibria. If θ_s becomes large, the condition becomes slack as large heterogeneity in consumption across workers of different incomes leads to more dispersion. I also emphasize that the condition under the special case ($\rho = 0$ and $\chi = 1$) is conservative since productivity spillover is purely local agglomeration and congestion force from land is small. Therefore, I consider the condition as a bound for the unique dynamic equilibrium conditional on the initial state. Online Appendix B.1 display the analytics for the special cases. I can characterize the dynamic equilibrium by the system of equations for *change* in variables between periods. I compute the dynamic path recursively from any state of the economy, and this is the tractable way to analyze the spatial dynamics featuring structural change, regional specialization and inequality. I describe the system of equations and solution methods in Online Appendix B.2. 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 (very) long run is characterized by the *stationary steady-state equilibrium* in which all aggregate variables are constant given that the exogenous time-varying factors ($\mathcal{F}_t$) are constant ($\mathcal{F}^*$). The following statement gives sufficient conditions for the uniqueness of the steady-state equilibrium in this economy.

PROPOSITION 1 *Suppose that there exists a sequence of fundamentals such that* $\mathcal{F}_t \to \mathcal{F}^*$*. Then, the stationary steady-state equilibrium exists. The steady-state is unique under the regularity conditions:*

$$\boldsymbol{\Upsilon} \geq 0, \quad \max_{s \in \mathcal{K} \setminus 0} \max_{(i,n) \in \mathcal{N} \times \mathcal{N}} \left| \frac{\partial \ln X_n^s}{\partial \ln L_i^s} \right| < 1,$$

$$\sup \left| \mathcal{E}_{ii}^s + \sum_{n \in \mathcal{N}} \frac{L_{in}^s}{L_i^s} \frac{\partial \ln \mathcal{E}_{in}^s}{\partial \ln L_i^s} \right| < 1, \quad \left| \sum_{(n,k) \neq (i,s)} \mathcal{E}_{in}^s \frac{\partial L_n^k}{\partial w_i^s} \right| \geq \max_{(\ell,s') \neq (i,s)} \left| \sum_{(n,k) \neq (i,s)} \mathcal{E}_{in}^s \frac{\partial L_n^k}{\partial w_\ell^{s'}} \right|$$

where $\boldsymbol{\Upsilon}$ *is matrix in which each entry is elasticity of export from local market* (i, s) *to wage of other local market* (ℓ, s')*.* $\mathcal{E}_{in}^s \equiv \lambda_{in|s} \cdot \varsigma_n^s$ *is transition probability for workers sorting into sector* s *and moving from* n *to* i*.*

The set of conditions argue the following. The first and second condition implies that linkage between local labor market through trade shows the regularity conditions. The third condition argues that labor mobility across space is large enough not to be clustered in one location, and the last condition is about the regularity condition for the linkage in local labor markets. In Online Appendix B.3, I show the manipulation of the system of equations for the steady-state equilibrium and discuss its uniqueness.

III.E Discussion of the assumptions and possible generalization

Efficient labor. The taste shock in the industry choice of workers in the model is isomorphic to the human capital specificity at industry level. Let $\boldsymbol{z}_t = \{z_{i,t}^s\}$ be a vector of idiosyncratic productivity that each worker can supply and suppose that individual determines the industry that gives highest return from work. Young generation receives the discrete number of productivity shocks and each value is drawn from Pareto distribution as in Assumption 2. Then, the share of workers that choose the industry is the same as in the baseline setting. The difference arises in the labor market clearing conditions.

Education. The baseline model abstracts any endogenous mechanisms that generate heterogeneity of labor supply and productivity among workers. I can extend the framework to include an explicit education choice. I allow workers 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. By introducing additional idiosyncratic factors in the net return of education, I can formulate the probabilities of education choice by similar representations. See Online Appendix A.5 for details.

Infinitely lived workers with perfect foresight. I consider individuals that work only in the second period of their life. Other approaches to see the dynamics entail infinitely lived workers with perfect foresight (McLaren 2017, Caliendo et al. 2019, Caliendo and Parro 2021, Kleinman et al. 2021). As I show in Online Appendix A.6, infinitely lived workers and households determine the future path of mobility in a forward-looking way, taking into account future shocks. Their choice of a given location is based on current real income but also an option value associated with that location. Comparing such approach and my model, *forward* solutions of the model upon the transitory shocks are different, and therefore different transitions arise. At the expense of forward-looking choices, my approach gives 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. Therefore, it is challenging to characterize the option values by sector and geography and discuss the intergenerational link (Krugman 1991, Matsuyama 1991, Ottaviano 1999, Baldwin 2001). It is also noted that there is the equivalence between the two approaches when considering the *backward* solution to back out the past fundamentals in the economy from the steady state. As shown in Online Appendix A.6, equilibrium dynamics are fully characterized by transition dynamics between two consecutive periods. Hence, we can solve the past states by backward from the steady state in both approaches.

IV Dynamics of Spatial Economy and Inequality

I now turn to the model's implication for the dynamics of local productivity, welfare and inequality by geography. I derive positive and normative analytical results regarding how common shocks or changes in exogenous fundamentals shape the spatial disparity of productivity, welfare, and inequality along with the transition. In this section, I use the notation for the change of equilibrium variables $\boldsymbol{x}_t$ such that $\mathrm{d}\ln \boldsymbol{x} \equiv \ln(\boldsymbol{x}_t/\boldsymbol{x}_{t-1})$.

Throughout this section, I assume that the fundamental amenities, sector-specific taste parameters and migration costs are unchanged: $\mathrm{d}\ln B^s_{i,t} = 0$, $\mathrm{d}\ln \zeta_{s,t} = 0$ and $\mathrm{d}\ln D_{in,t} = 0$. In subsection IV.A, I first consider the transition dynamics for the total factor productivity (TFP) in local economy and its spatial variation, then I discuss welfare gains and losses in the transition. After that, in subsection IV.B, I derive the model's implications for the dynamics of the equilibrium prices in the local labor market and immobile factors. Lastly, the model's simple framework speaks to inequality in the local labor market and intergenerational mobility in subsection IV.C. Details associated with these analytical results are in Online Appendix C. In the last subsection IV.D, I describe the numerical results of equilibrium to explore the pattern of structural transformation and inequality on the simple economy. I also present some numerical results for comparative statics.

IV.A Measured Local TFP and Welfare Dynamics

I explore the role of spatial linkages of trade and labor mobility in the evolution of the local TFP and its spatial variation. I refer to $\delta^s_{i,t}$ as the local TFP of sector s in location i.

The first objective is to see how exogenous shocks in the economy change the local level TFP differently by geography. Intuitively, 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. I also derive the steady state level of local TFP. The following 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:*

$$\frac{\mathrm{d}\ln \delta^s_{i,t}}{\mathrm{d}\ln A^s_{i,t}} = 1 - \frac{1}{\kappa_s}\frac{\mathrm{d}\ln \pi^s_{ii,t}}{\mathrm{d}\ln A^s_{i,t}} + \sum_n \left(\rho \widetilde{z}^s_{in,t} + \gamma_s \widetilde{l}^s_{in,t}\right)\left(\frac{\mathrm{d}\ln \lambda_{in|s,t}}{\mathrm{d}\ln A^s_{i,t}} + \frac{\mathrm{d}\ln \varsigma^s_{n,t}}{\mathrm{d}\ln A^s_{i,t}}\right)$$

where $\widetilde{z}^s_{in,t} \equiv \frac{L^s_{in,t} Z^s_{n,t-1}}{\sum_\ell L^s_{i\ell,t} Z^s_{\ell,t-1}}$ is the contribution of location n in the baseline equilibrium; and $\widetilde{l}^s_{in,t} \equiv \frac{L^s_{in,t}}{\sum_\ell L^s_{i\ell,t}}$ is the share of workers' inflow. In the steady state, the local TFP converges to:

$$\ln \delta^s_i = -\frac{1}{\kappa_s}\ln \pi^s_{ii} + \sum_n K^s_{in}\Big(\ln A^s_n + (\gamma_s + \rho)\ln L^s_n + \rho \Delta^s_n\Big)$$

where K^s_{in} is (i,n)-th element of the matrix $\mathbf{K}^s \equiv \sum_{m=0}^{\infty} \rho^m \left\{\lambda_{in|s}\varsigma^s_n \widetilde{l}^s_{in}\right\}^m$ and Δ^s_i is small positive constant.

To a common shock to the technology of sector s in the economy at period t, the second term reflects the gains from trade: an increase of local TFP is associated with more export to other locations. A small trade elasticity (κ_s) leads to a large variation of local TFP gains *ceteris paribus*. The third term conflates the scale effect and spillover from the in-migration of workers. A large value of scale economies (γ_s) 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. These margins are key mechanisms that create the heterogeneous transition of productivity in the local labor markets when there is a common shock. In the steady state, the first term captures the comparative advantage in trade, and the matrix $\{K_{in}\}$ is the matrix summarizing the linkages between productivity in other locations and the local labor market. See Online Appendix C.1 for details.

Next, I consider the welfare dynamics in the transition of the economy. My interests are the spatial difference in welfare change and its decomposition into margins in the model. To this end, I use $V_{i,t}$ in (7) as a measure of welfare for individuals of generation t who have origin i. This measure is *ex-ante* average real income conditional on the previous employment distribution.[19] Then, I can represent the welfare change of individuals between two consecutive generations of workers who have the same origin.

PROPOSITION 3 *In the dynamic equilibrium, change of welfare measure over generations* $\mathrm{d}\ln V_{i,t}$ *is proportional to:*

$$\sum_{s\in\mathcal{K}\backslash 0}\left(-\frac{\mathrm{d}\ln\lambda_{ii|s,t}}{\epsilon}-\frac{\mathrm{d}\ln\varsigma^s_{i,t}(L^s_{i,t-1})^{-\eta}}{\phi}+\widetilde{\theta}_s\left(\frac{\mathrm{d}\ln e^s_{s|i,t}}{1-\sigma}+\beta_s\sum_j\widetilde{\beta}_{sj}\mathrm{d}\ln\frac{\delta^j_{i,t}}{w^j_{i,t}}-(1-\beta_s)\sum_j\widetilde{\beta}_{sj}\frac{\mathrm{d}\ln\pi^j_{ii,t}}{\kappa_j}\right)\right)$$

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

See Online Appendix C.2 for details of derivation. The presented framework has essential margins that determine the spatial variation of welfare changes ($\mathrm{d}\ln V_{i,t}$). The first term is the change in non-migration probability with elasticity $-1/\epsilon$. Conditional on the sector choice, $\mathrm{d}\ln\lambda_{ii|st}$ 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 $\epsilon\to\infty$, idiosyncratic shocks in location choice are homogeneous, and gains from migration become zero. The second source of welfare dynamics is the change of the industry choice of workers. The second term ($-\mathrm{d}\ln\varsigma^s_{i,t}/\phi$) 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 (ς^s_i) implies the 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 choice 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. This part is related to welfare gains in international trade. Namely, without factor mobility via migration ($\epsilon\to\infty$), self selection in industry choice ($\phi\to\infty$), and non-homotheticity ($\widetilde{\theta}_s=1$), this is collapses to multi-sector extension of Arkolakis et al. (2012). Comparing the non-homothetic demand and homothetic demand ($\widetilde{\theta}_s=1$), 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., $\widetilde{\theta}_s>1$), 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 give an incentive for workers to move to the local labor market, and production relocates to the place

[19] It is important to note that, in my model, the ex-ante expected utility among cohort t also includes the Lagrangian multiplier associated with (5). The multiplier is determined by the employment composition of the previous generation $t-1$. However, I do not include the multiplier in the measure of welfare since it does not affect the choice probabilities of workers.

in response to the productivity changes and demand shift. The spatial linkages between local labor markets determine the distributional effects of TFP change and welfare change over time.

At this point, I can consider the welfare loss from the migration barrier. The following augment states that the role of labor mobility and its relation to the variation of sector choice:

LEMMA 1 *Suppose that any particular generation faces $D_{in,t} = 1$ for all $i \neq n$. If $\phi < \infty$, welfare growth from eliminating migration barrier is strictly small compared to the limit case as $\phi \to \infty$.*

I can evaluate the welfare loss from migration cost by the $\mathrm{d}\ln V^F_{i,t} - \mathrm{d}\ln V_{i,t}$ where $\mathrm{d}\ln V^F_{i,t}$ is the welfare when migration barrier is eliminated, $D_{in,t} = 1$ for all i and n. Eliminating migration frictions allow workers to choose the sector that exhibits the highest average real income in the economy, as average real income is equalized across locations. When $\phi \to \infty$, workers have less specificity ex-ante location choice. Ex-ante labor specificity makes it difficult to adjust the labor supply in the future, taking into account the sector-level average utility change. Consequently, gains from eliminating migration frictions are large when workers are homogeneous as $\phi \to \infty$ compared to the baseline.

IV.B Measures of Local Market Dynamics

I now consider features of the model that determine the transition of local labor markets. The key measures for the local labor market are twofold. First, employment distribution is given by the share of employment across industries, $f^s_{i,t} \equiv L^s_{i,t} / \sum_{k \in \mathcal{K}} L^k_{i,t}$ and its variation across space represents the geography of structural transformation. Another one is the fraction of income for different industries $y^s_{i,t} \equiv w^s_{i,t} L^s_{i,t} / \sum_{k \in \mathcal{K}} w^k_{i,t} L^k_{i,t}$ characterize the income distribution. These two measures are the sufficient statistics of the local labor markets. Lastly, the dynamics of price for immobile factor explains the source of spatial variation of housing price and land price.

Local labor market. By definition, the change of employment ($\mathrm{d}\ln \mathbf{L}$) and change of income ($\mathrm{d}\ln \mathbf{Y} = \mathrm{d}\ln \mathbf{w} + \mathrm{d}\ln \mathbf{L}$) characterize the change of the fraction of employment ($\boldsymbol{f} = \{f^s_{it}\}$) and income ($\boldsymbol{y} = \{y^s_{i,t}\}$) conditional on previous equilibrium state. The employment evolves by location and industry choice of workers (12), and labor market clearing condition for each industry and location pins down income distribution that is consistent with the employment growth in the local labor market. Based on the initial distribution of employment and income in the economy, I obtain their transition dynamics of wages by the closed-form representation as follows:

PROPOSITION 4 *Suppose that $\mu_{i,t} = 1$. Then, wage growth for generation t satisfies:*

$$\mathrm{d}\ln w^s_{i,t} = \sum_j \Lambda^{sj}_{i,t-1} \left(-\frac{\mathrm{d}\ln \bar{\psi}^j_{i,t}}{1-\sigma} + \frac{1}{\epsilon} \frac{\bar{\theta}_{i,t-1} - \sigma}{1-\sigma} \sum_n \widetilde{\lambda}_{in|j,t-1} \mathrm{d}\ln \lambda_{nn|j,t} \right) - \Lambda^s_{i,t-1} \left(\sum_j \widetilde{\Psi}^j_{i,t-1} \mathrm{d}\ln \delta^j_{i,t} \right)$$

where I use the following notations: $\bar{\psi}^s_{i,t} \equiv \prod_j (\psi^s_{j|i,t})^{\Psi^j_{i,t-1}}$ is weighted geometric mean of expenditure share for each type of worker with expenditure share on s among tradable goods in previous period $\Psi^s_{i,t-1}$, $\bar{\theta}_{i,t-1} = \sum_j \Psi^j_{i,t-1} \theta_j$ is weighted average of Engel slope, $\widetilde{\lambda}_{in|j,t-1}$ is an element of matrix $\left(\mathbf{I} - \{\lambda_{ni|j,t-1}\}^\top_{n,i}\right)^{-1}$, $\widetilde{\Psi}^j_{i,t-1} \equiv \sum_s \Psi^s_{i,t-1} \widetilde{\beta}_{sj}$, $\Lambda^{sj}_{i,t-1}$ is the element of matrix $\left(\mathbf{I} - \{\beta_j \widetilde{\Psi}^j_{i,t-1}\}_{j,j}\right)^{-1}$, and $\Lambda^s_{i,t-1} = \sum_j \Lambda^{sj}_{i,t-1}$.

See Online Appendix C.3 for details and more general discussion. To keep the discussion clear, I assume that the revenue from land goes to landlords absent in the economy. This proposition states how wage evolves.

I consider a change of productivity over time but keep labor mobility costs fixed and assume land development revenue is distributed to the absentee landlords. Then, the wage dynamics combine the Rybczinski derivatives and the Stolper-Samuelson derivatives in the spatial economics framework. In the first term on the right-hand side, the pre-determined elements $\{\Lambda^{sj}_{i,t-1}\}$ summarize the substitution of labor between sector s and j. Hence, the first term explains the effect of increased migration of workers in industry j on the wage of industry s. Within the parenthesis, the first term is about the workers' heterogeneity in consumption. Analytically, $\{\bar{\psi}^{j}_{i,t}\}$ evaluates the distortion in expenditure patterns relative to the uniform expenditure share. The second term factors the change of real income and the slope of the local Engel curve. When considering homothetic demand system, $\bar{\theta}_{i,t-1} = 1$ and this term is reduced to pure change of real income, $\mathrm{d}\ln \mathcal{W}^{j}_{i,t}$. These two terms together determine the expansion of labor in industry j in the location i, and its impact on industry s depends on the labor intensity in production. Hence, this term is about the Rybczinski derivatives. The second parenthesis on the right-hand side states the relationship between TFP changes and wage growth. As I discussed in Proposition 2, change in the import penetration and productivity contribute to the change in TFP. Therefore, the matrix $\mathbf{\Lambda} = \{\Lambda^{s}_{i,t-1}\}$ gives information of the Stolper-Samuelson derivatives that summarizes how the change in trade pattern affect the wage. The input-output linkages and expenditure patterns together characterize the derivative. These two derivatives determine wage changes to the common shocks in the economy. The differences in elements $\{\Lambda^{s,j}_{i,t-1}\}$ govern the difference in wage growth between industries, and the spatial variation of wage growth results from the variation in the probabilities of labor reallocation (i.e., migration) and trade conditional on the local expenditure patterns.

Price of immobile factors. The immobile good – residential stocks – is essential as a dispersion force for workers in the economy. In the model, the stock of residential structure shows the dynamics that reflect the demand heterogeneity for housing. To account for the demand heterogeneity across workers, I let $\boldsymbol{\xi} = \{\xi^{s}_{i,t-1}\}$ refer to the matrix whose elements are the pre-period share of housing demand by workers in industry s. The following statement presents the mapping from land rent and income distribution to the price dynamics of the housing:

PROPOSITION 5 *Suppose that $\mu_{it} = 1$. The dynamics of housing price, to a first order term, is given by:*

$$\sigma \mathrm{d}\ln \widetilde{p}^{0}_{i,t} = -\chi \mathrm{d}\ln L^{0}_{i,t} + \mathrm{d}\ln r_{i,t} + \sum_{s\in\mathcal{K}} \xi^{s}_{i,t-1}\Big[(\mathrm{d}\ln y^{s}_{i,t} - \mathrm{d}\ln y^{0}_{i,t}) + (\theta_0 - \bar{\theta}_{i,t-1})\mathrm{d}\ln \mathcal{W}^{s}_{i,t} + \mathrm{d}\ln \bar{\psi}^{s}_{i,t}\Big]$$

where $\widetilde{p}^{0}_{i,t} \equiv p^{0}_{i,t}/\bar{p}_{i,t}$ is relative price of housing, $\widetilde{r}_{i,t}$ is relative land rent, and $\bar{p}_{i,t}$ is Törnqvist price index using the pre-period expenditure share.

This proposition allows me to isolate different channels behind the spatial heterogeneity of housing price changes. See Online Appendix C.4 for derivation. On the right-hand side, the first and second terms are standard mechanisms of housing supply. When the supply of housing is inelastic, $\chi = 0$ in the first term. The direct pass through of land prices is given by $1/\sigma$. The third term combines the change of income distribution, the change of real income, and the shift of expenditure share. An increase in the income share of workers of the industry s showing higher demand for residential structure leads to an increase of relative price, $\widetilde{p}^{0}_{i,t}$. Therefore, this term captures the relationship between the change of local income inequality and housing price change. The next term is a change of real income associated with labor mobility. Suppose Engel slope of housing (θ_0) is smaller than the average level ($\bar{\theta}_{i,t-1}$). Then, a low probability of staying in the place is associated with increased housing prices since a stronger congestion force induces higher gains of migration to other locations. The last term is the change of expenditure shares: large consumption inequality is associated with an increase in housing prices, *ceteris paribus.* Apart from the traditional channels of the heterogeneity of housing supply, the transition dynamics of the income distribution, labor mobility, and consumption disparity across workers create the fluctuation in the housing price index.

IV.C Dynamics of Inequality

Given the dynamics of prices, I am now in the position to discuss income inequality among individuals. The first aspect of income inequality is the cross-sectional inequality among workers in any particular location. This *within-location* inequality may change over time in response to the structural transformation. The second focus is *income mobility*. The model, by its nature, can speak to the degree of upward mobility in the income distribution relative to the previous generation.

Inequality. The probability mass function $(\{y^s_{i,t}\})$ gives the income distribution of workers in location i during period t. The share of workers in place i that receives a certain income level is equal to the share of workers in the relevant industry. Therefore, the measure of income inequality in each location is fully characterized by industry employment share and industry income share. As I discuss in Online Appendix C.5, these two measures are sufficient statistics to evaluate intra-location income inequality by different widely used measures that take a form of:

$$\mathcal{I}_{it} = \sum_{s\in\mathcal{K}} f^s_{it} G\left(\frac{y^s_{it}}{f^s_{it}}\right)$$

where $G(\cdot)$ is an arbitrary function corresponding to different measures, including coefficient of variation, Gini coefficient, and Theil index. Change in employment share ($\boldsymbol{f}$) affects the income inequality through the composition effect of workers conditional on the ex-ante wage difference in the local labor market, and the relative wage change across industries is captured in y^s_{it}/f^s_{it} as it is identical to the slope of the Lorenz curve in the model. To see the mechanisms at work, I focus on the coefficient of variation where the function $G(\cdot)$ is multiplicative decomposable.

PROPOSITION 6 *Consider the measure of income inequality based on the coefficient of variation. The change of income inequality at the local level over generations is:*

$$\mathrm{d}\ln \mathcal{I}_{i,t} = \sum_{s\in\mathcal{K}} \iota^s_{i,t-1} \mathrm{d}\ln G^s_{i,t} - \underbrace{\sum_{s\in\mathcal{K}} \left(y^s_{i,t-1} - f^s_{i,t-1}\right) \mathrm{d}\ln L^s_{i,t}}_{\text{Composition effect}}$$

with

$$\mathrm{d}\ln G^s_{i,t} = \underbrace{\mathrm{d}\ln \widetilde{Y}^s_{i,t}}_{\text{Industry}} - \underbrace{\frac{\eta}{\phi}\frac{\theta_0-\sigma}{1-\sigma}\mathrm{d}\ln \widetilde{L}^s_{i,t-1}}_{\text{Persistency}} + \underbrace{\frac{1}{\phi}\frac{\theta_0-\sigma}{1-\sigma}\mathrm{d}\ln \widetilde{\varsigma}^s_{i,t}}_{\text{Sectoral choice}} + \underbrace{\frac{1}{\epsilon}\frac{\theta_0-\sigma}{1-\sigma}\mathrm{d}\ln \widetilde{\lambda}^s_{ii,t}}_{\text{Location choice}} - \underbrace{\frac{1}{1-\sigma}\mathrm{d}\ln \widetilde{\boldsymbol{\psi}}^s_{0|i,t}}_{\text{Expenditure on housing}}$$

where $\iota^s_{i,t-1}$ is the contribution of sector s in the income inequality among previous generation $t-1$, and let $\widetilde{x}^s_{i,t}$ refers the transformed variables using previous income share such that $\widetilde{x}^s_{i,t} \equiv \frac{x^s_{it}}{\prod_{s\in\mathcal{K}}(x^s_{it})^{y^s_{it-1}}}$.

See Online Appendix C.5 for derivation. This proposition illustrates how income inequality in the local market is related to spatial structural change. The composition effect is a standard: employment shift from industry with relatively lower wage to higher wage suppress the inequality. Other than this, relative growth of industry $(\mathrm{d}\ln \widetilde{\boldsymbol{Y}}_t)$, pre-trend of employment growth $(\mathrm{d}\ln \widetilde{\boldsymbol{L}}_{t-1})$, change of workers' sorting pattern in the sectoral choice $(\mathrm{d}\ln \widetilde{\varsigma}_t)$, difference in no-mobility workers $(\mathrm{d}\ln \widetilde{\boldsymbol{\lambda}}^{\mathbf{N}}_t)$ and difference in expenditure share in housing

($d \ln \widetilde{\psi}_t^0$) shift the income inequality together. First, the industrial agglomeration creates the uneven labor adjustment process across industries in the first and second terms. With $\eta = 0$, there is no *direct* effect of persistency in the adjustment of factor specificity. The relative wage growth in the sector is positively associated with the sector's contribution to an expansion of income inequality. If I assume no heterogeneity in sectoral choice ($\phi \to \infty$), these mechanisms of factor specificity are absent in the change of income inequality. A small probability of staying in the place is positively associated with a change in income inequality. When idiosyncratic shocks are more heterogeneous ($\epsilon \to 1$), its contribution becomes large as workers must face a large gap in wage growth to stay conditional on industry choice. The last term says that the strong congestion force counteracts the positive composition effects. Given that congestion forces are substantial when more substitutes, this countereffect is magnified by lower $1 - \sigma$.

So far, Proposition 6 gives the general equilibrium relationship between the different trends of income inequality in local labor markets along with spatial structural transformation, factor specificity, and labor mobility.

Upward mobility. The model gives a simple framework to argue the relationship between spatial structural change 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 I have no explicit inter-generational link between specific pair of parents among generation $t - 1$ and children among generation t.[20] Nevertheless, my model emphasizes the structure of local labor markets and mobility between them.[21] Therefore, the model enables me to focus on the importance of location choices and sector choices in shaping the geography of intergenerational mobility. In particular, the model allows me to characterize (i) income distribution of generation t (i.e., parents) in each location, and (ii) income distribution of generation $t + 1$ (i.e., children) who have the same origin. Using them, I assess the general equilibrium relationship of *income distribution* between parents and children in each location.[22]

I start with the discussion of the measure. I let $\mathcal{R}^{\mathbf{o}}_{i,t}$ be the mean of percentile in the national income distribution for generation t working in location i, and $\mathcal{R}^{\mathbf{y}}_{i,t+1}$ refers to the *expected* percentile in the national income distribution for the next generation who are born in location i. Using these measures, the baseline index of intergenerational mobility for individuals in location i between generation t and $t + 1$ is:

$$\mathcal{M}_{i,t+1} = \mathcal{R}^{\mathbf{y}}_{i,t+1} / \mathcal{R}^{\mathbf{o}}_{i,t} \tag{16}$$

The ratio $\mathcal{M}_{i,t+1}$ is 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, $\mathcal{M}_{i,t+1}$ returns a high value.

In the model, the measure (16) is fully characterized by the variables in equilibrium. The upward mobility increases when workers of generation $t + 1$ sort into the industry with high wage growth and move to the location with relatively high wages and large surplus from land. The first effect is controlled by the probability of industry choice, and the second effect hinges on the expected value of relative income in the destination to the origin. The average upward mobility (16) compounds these two forces. I summarize the relationship

[20] Besides, I abstract the details in the decision of human capital accumulation in the baseline model, and I do not impose a detailed structure on the lifecycle of individuals. See discussion in III.E for them.

[21] This is the similar attitude of Huttunen et al. (2018) that emphasizes the structure of the local labor market and idiosyncratic factors (e.g., family ties) in migration decisions, which turns out to be persistent of income difference across locations.

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

between the measure and the equilibrium of the model in the following proposition:

PROPOSITION 7 *Define the income distribution in the whole economy $\mathcal{Q}_t$ such that:*

$$\mathcal{Q}_t(W^s_{i,t}) = \sum_{n\in\mathcal{N}}\sum_{j\in\mathcal{K}} f^j_{n,t}\mathbb{I}[W^j_{n,t} \leq W^s_{i,t}]\frac{L_{n,t}}{\bar{L}} \equiv \mathcal{Q}^s_{i,t}$$

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

$$\mathcal{M}_{i,t+1} = \sum_{s\in\mathcal{K}} \varsigma^s_{i,t+1}\left(\sum_{n\in\mathcal{N}}\lambda_{ni|s,t+1}\frac{\mathcal{Q}_{t+1}(W^s_{n,t+1})}{\sum_{j\in\mathcal{K}} f^j_{i,t}\mathcal{Q}_t(W^j_{i,t})}\right), \tag{17}$$

I can compute the measure for the equilibrium in a straightforward way, and the measure (17) is very intuitive. It is useful to see the decomposition of this measure into the different margins in the model:

$$\mathcal{M}_{it+1} = \sum_{s\in\mathcal{K}} \underbrace{\varsigma^s_{it+1}}_{\text{Job Opportunity}} \underbrace{\frac{\mathcal{Q}^s_{it}}{\sum_{k\in\mathcal{K}} f^k_{it}\mathcal{Q}^k_{it}}}_{\text{Local Inequality}} \underbrace{\frac{\mathcal{Q}^s_{it+1}}{\mathcal{Q}^s_{it}}}_{\text{Local Growth}} \underbrace{\left[\sum_{n\in\mathcal{N}}\lambda_{ni|st+1}\frac{\mathcal{Q}^s_{nt+1}}{\mathcal{Q}^s_{it+1}}\right]}_{\text{Spatial Mobility}} \tag{18}$$

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 on geography is the consequence of the different extent of structural change, and evaluate the importance of spatial economy regarding how further the young generation can climb up on the income ladder.

I can define alternative measures for intergenerational income mobility. One index is related to absolute upward mobility: what is the likelihood of earning more than parents? I can represent them by the probability of earning higher than a worker at α-th quantile in the previous generation with any particular value of α. Another measure captures the upward mobility from the bottom to the top by comparing the workers at the bottom of the quantile and the top of the quantile. Intuitively, a large value of such index in particular place i implies that the top income individuals arise from the cohort of generation $t+1$ born in location i where workers in the previous generation are relatively lower income group at the national level. Therefore, this can be seen as the "American Dream." See Online Appendix C.6 for discussion on these measures. As a baseline, however, I use (17) since it is robust and shows continuity over time compared to other measures.

IV.D Numerical Illustration of a Dynamic Equilibrium

In this subsection, I provide a numerical illustration of an equilibrium. The goal is to understand the equilibrium implications I discussed above more concretely. To this end, I consider the simplest spatial economy. Imagine the hypothetical one-dimensional space (i.e., line) in which there are discrete locations over unit space. They locate with even geographical intervals. Specifically, there are 250 discrete locations over unit space $[0, 1]$. The simulation requires specifications for some fundamental environment and parameters in the model. I briefly discuss the key settings here and Online Appendix D summarizes other details.

There are four sectors: manufacturing (M), non-tradable service (R), tradable service (S), and construction (C). The construction sector corresponds to sector 0 in Section III. The elasticity of substitution between sectors is 0.4 and sector-specific income elasticities are set to be in line with Comin et al. (2020) such that the tradable service sector shows a larger value of Engel slope compared to non-tradable service. I set trade elasticity equalized across sectors: $\kappa = 6.0$. I abstract input-output linkage for simplicity, therefore labor is the only input in production. The static scale effects are set to be $\gamma_{\mathrm{M}} = \gamma_{\mathrm{S}} = \gamma_{\mathrm{NS}} = 0.20$, and I abstract the spillover in productivity ($\rho = 0$). For the construction sector, I set the depreciation rate of structure, 0.20, and labor share is $\chi = 0.35$. For the choice of workers in labor supply, there are three parameters. The parameter ϵ captures the elasticity of labor mobility across different locations to real income. Following Fajgelbaum et al. (2019), I set $\epsilon = 1.5$. The next parameter, ϕ, captures the elasticity of industry choice to the return from the choice of industry. I assign $\phi = 2.5$. Lastly, I set $\eta = 0.80$ as a benchmark. These values are similar to values I adopt in Section V.

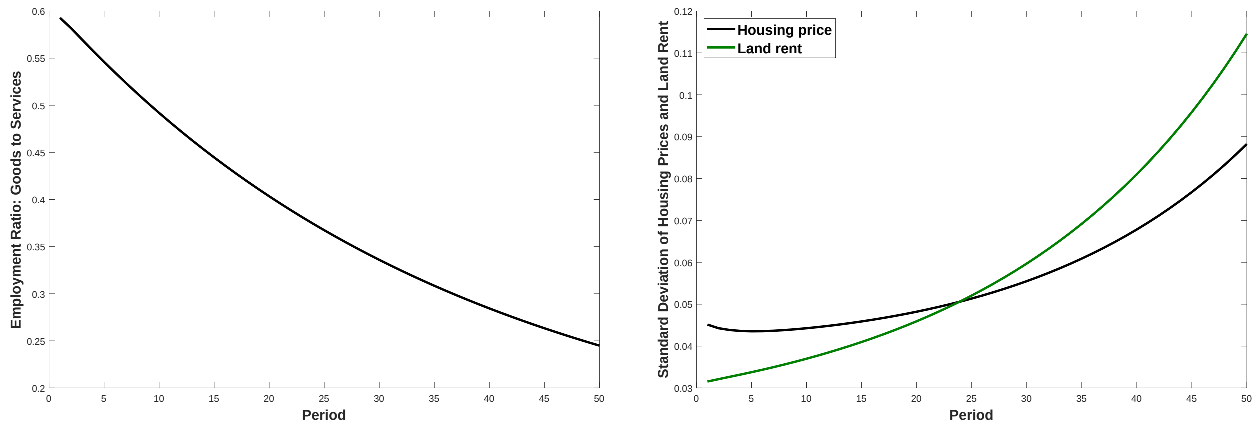
An exogenous environment is as follows. I turn off the spatial variation in amenities and land endowment is homogeneous across space. Assume that initial fundamental productivity is high in the left edge of the space and monotonically decreases to the other edge of the space. This rationalizes the concentration of manufacture in the early period and enables to eliminate the potential multiplicity of equilibria.[23] I let the exogenous productivity for the manufacturing sector grow at the exogenous rate in each period, while exogenous productivity growth is absent for other sectors. I parametrize migration costs and trade costs. The bilateral migration cost between location i and n is proportional to geographical distance $D_{in,t} = \exp(d|i-n|)$. I assign $d = -\ln 0.5$ that implies the remaining of utility after moving from the edge to edge is 50 percent. The bilateral trade cost takes a form of $\tau^j_{in,t} = \exp\big(\tau^j|i-n|\big)$ with sector j's efficiency of transportation τ^j. Set $\tau^{\mathrm{M}} = \tau^{\mathrm{S}} = 0.15$ for manufacturing and tradable services, while $\tau^{\mathrm{R}} = 1.0$, so that non-tradable services are much less tradable compared to manufacturing and tradable sector. For the initial state, without further information, I assume that the initial equilibrium is consistent with the long-run steady state.

I first describe the baseline equilibrium and then proceed to see different scenarios. Figure 5 displays the structural change and variation in housing prices in the aggregate economy. Panel 5a confirms the shift of aggregate employment from goods (manufacturing sector and construction sector) to services (non-tradable service and tradable service). The employment ratio of goods to services declines over time, driven by the productivity growth of the manufacturing sector and nonhomothetic demand. Panel 5b shows the standard deviation of housing prices and land rent. The spatial variation of housing prices increases as the agglomeration of services arises in the right edge of space along with the decline of the manufacturing sector. Figure 6 shows the distribution of workers for three sectors. The gradation represents the share of employment in each sector for any particular location. The left edge locations keep the manufacturing sector's comparative advantages over time but move to service sectors. On the other hand, the right edge cities show specialization of nontradable services in early stages with shrinking of the manufacturing sector. This leads to demand shift to tradable service sectors due to non-homothetic preference. Therefore, the right cities give rise to tradable services. In the later period, the right-edge cities are specializing tradable services and the right-central cities see the agglomeration of nontradable services. The difference in the location of agglomeration between panel 6b and 6c is due to the difference in trade costs.

Figure 7 graphics the welfare change for individuals between two generations. The first panel 7a shows welfare difference between generations ($\mathrm{d}\ln V_{i,t}$). The overall welfare change for workers is high in the right edge places. The other three panels give the different margins to determine the welfare changes as I discussed in Proposition 3. Panel 7b shows that the left places exhibit larger gains for workers from migration to the

[23] Suppose I assume a uniform distribution of fundamental productivity. In that case, potentially multiple equilibria arise where one sector is concentrated in either the central place or the edges.

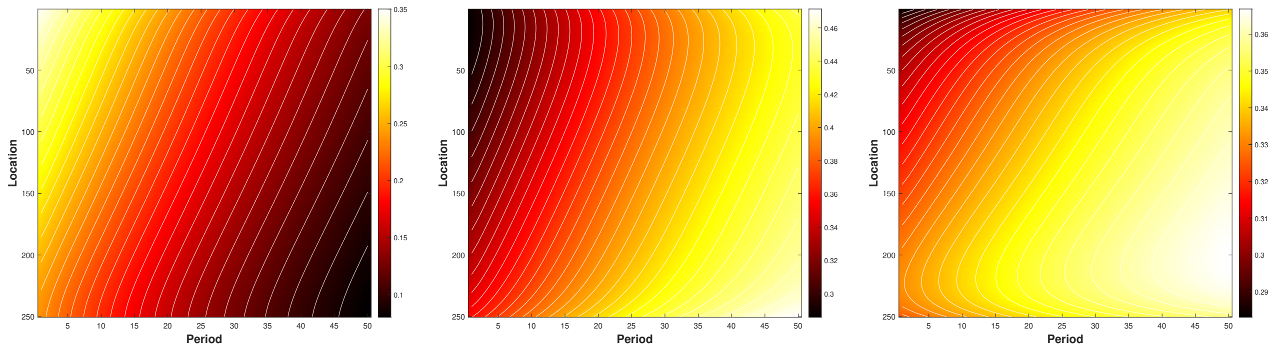
Figure 5: Structural Change and Variation of Housing Prices



(a) Aggregate Employment Change

(b) Variation of Housing Prices and Land Rent

Figure 6: Geography of Structural Change



(a) Manufacturing

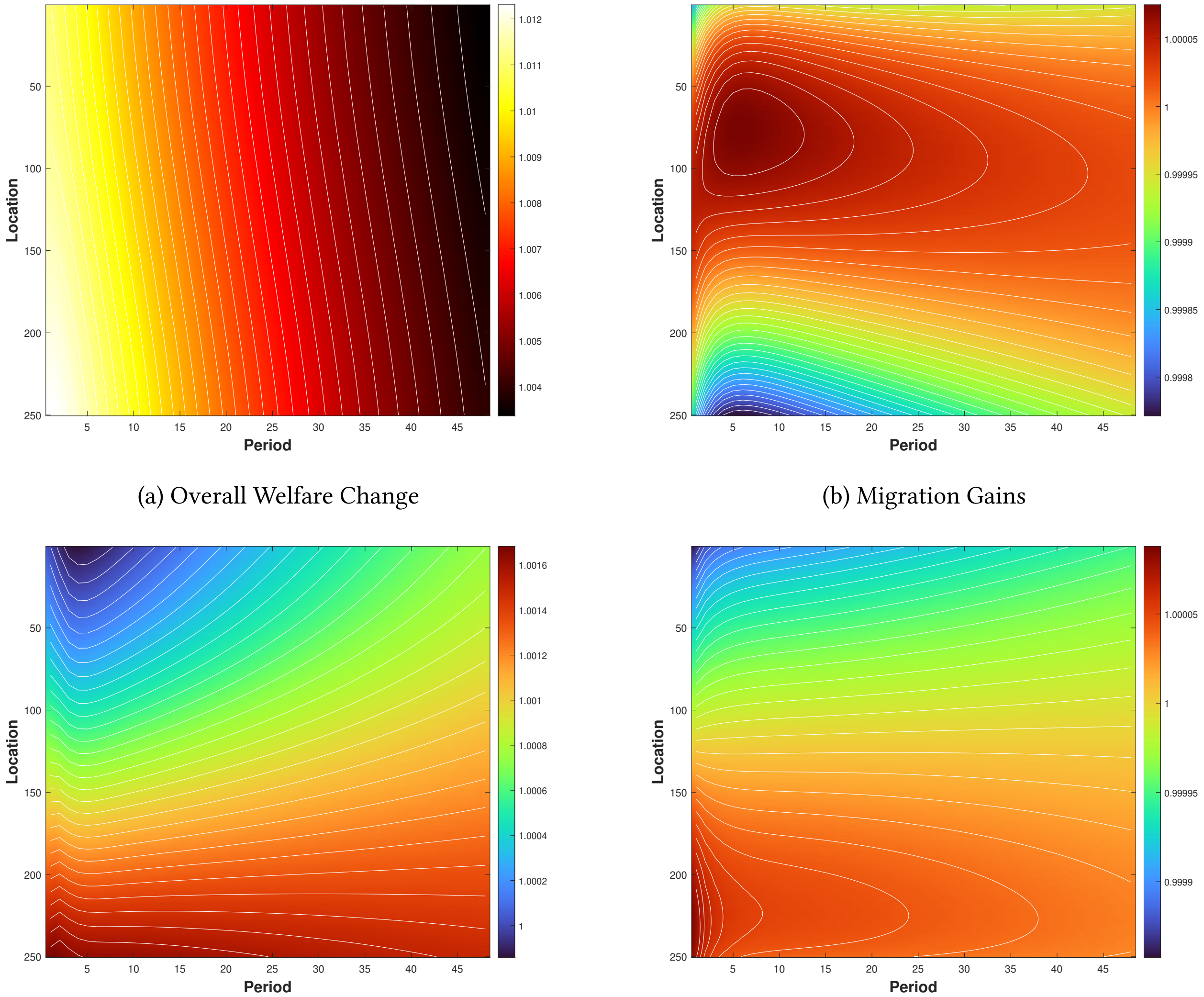
(b) Tradable Service

(c) Nontradable Service

right locations where real income is high, and such gains decline over time as service sectors are dispersed in the later period. Panel 7c shows the spatial variation of gains from job opportunities. Individuals in the hot-colored locations benefit from the local labor markets in their choice of the sector. This margin takes an important role in the overall welfare changes in its magnitude. In contrast, individuals in the left-edge cities benefit less. The logic is clear; a higher probability to sort into the manufacturing sector leads to less opportunity to move to other labor markets. The last Panel 7d shows the gains from trade. The right cities are net exporters of services to the left cities so that the measure of gains from trade exhibits large values in these areas. These three margins are compounded in the overall welfare changes in Panel 7a.

Next, I show inequality and upward mobility in Figure 8. Panel 8a confirms the intuition in Proposition 6. In the initial period, the left-edge cities show a concentration of the manufacturing sector, leading to lower inequality compared to the right places. Conditional on this fundamental pattern of sectoral contribution in income inequality, persistency of sorting and lower mobility keep the income inequality in the right cities high. I investigate the implication of upward mobility in Panel 8b where I show the measure of the intergenerational mobility proposed in Proposition 7, $\ln \mathcal{M}_{i,t+1}$. I find that there is a huge difference in intergenerational mobility over space. In early periods, workers who originate from the service cities in the right area can climb up the position of income distribution compared to manufacturing cities. They are able to migrate to other cities and sort into the service sector with high likelihood. The central places exhibit the lowest upward mobility over time. The logic behind this is the low degree of dynamics among workers in the central places for both location choice and sector choice. Ultimately, the service cities exhibit lower upward

Figure 7: Welfare Changes



(a) Overall Welfare Change

(b) Migration Gains

(c) Job Opportunity Gains

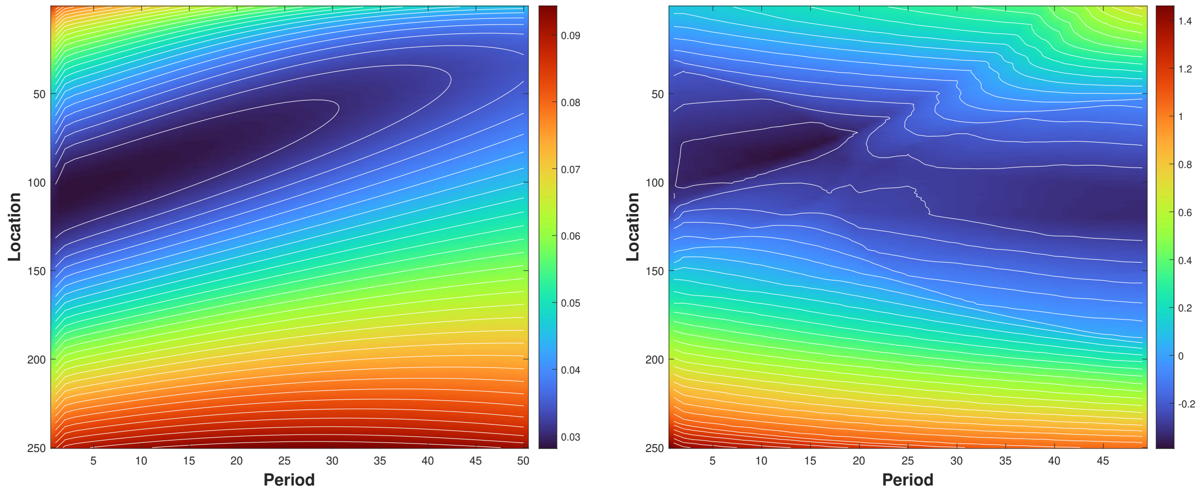
(d) Trade Gains

mobility of workers. This is intuitive. In these cities, the service sector grows and more workers sort into both sectors of service. Then, conditional on the job opportunity, the change in the position of the income ladder becomes small. In contrast, the left-edge cities show higher upward mobility in the later period. This is because of the structural change from manufacturing to services and the spread of service sectors to the left cities where individuals from left-edge cities can move into.

IV.D.I Productivity Shock and Migration Costs

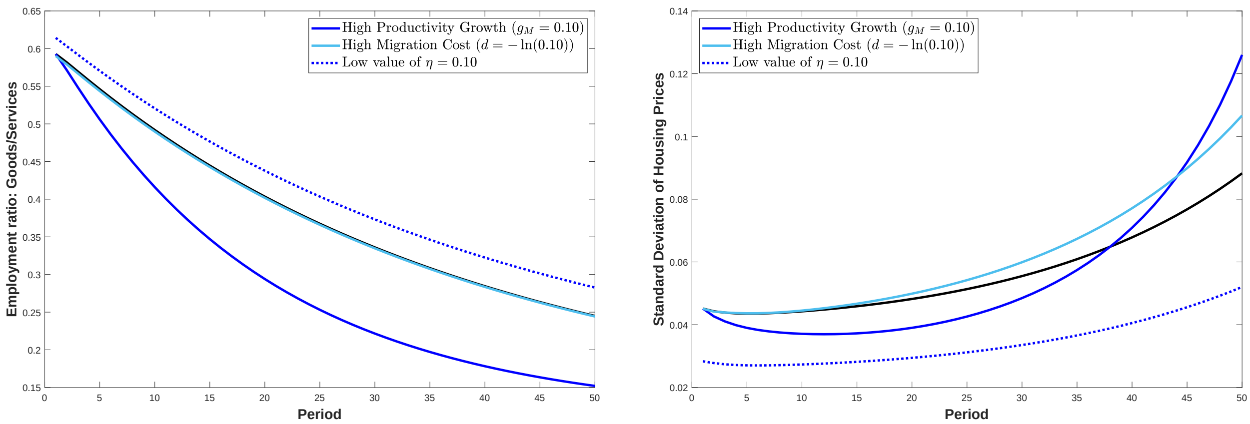
Next, I consider the different two scenarios in the simple economy. First, suppose that there is technological progress in the manufacturing sector. In the baseline, I assume that the fundamental productivity of manufacturing grows at 5 percent each period. I now set 10 percent for the growth rate. Intuitively, this captures the continuous innovation in the manufacturing sector. Second, I consider high migration costs. In the baseline, I set $d = -\ln 0.5$. Now, I set $d = -\ln 0.1$, which implies that only 10 percent of utility remains when individuals migrate from the edge city to the other edge city. For these two scenarios, I consider how cross-sectional inequality and upward mobility are changed. In Figure 9, the left-hand panel 9a shows the change of employment ratio corresponding to Figure 5a, and the right-hand panel 9b shows the variation of

Figure 8: Inequality and Upward Income Mobility



(a) Coefficient of Variation in Income (b) Upward Mobility: $\ln \mathcal{M}_{i,t+1}$

Figure 9: Different Scenarios

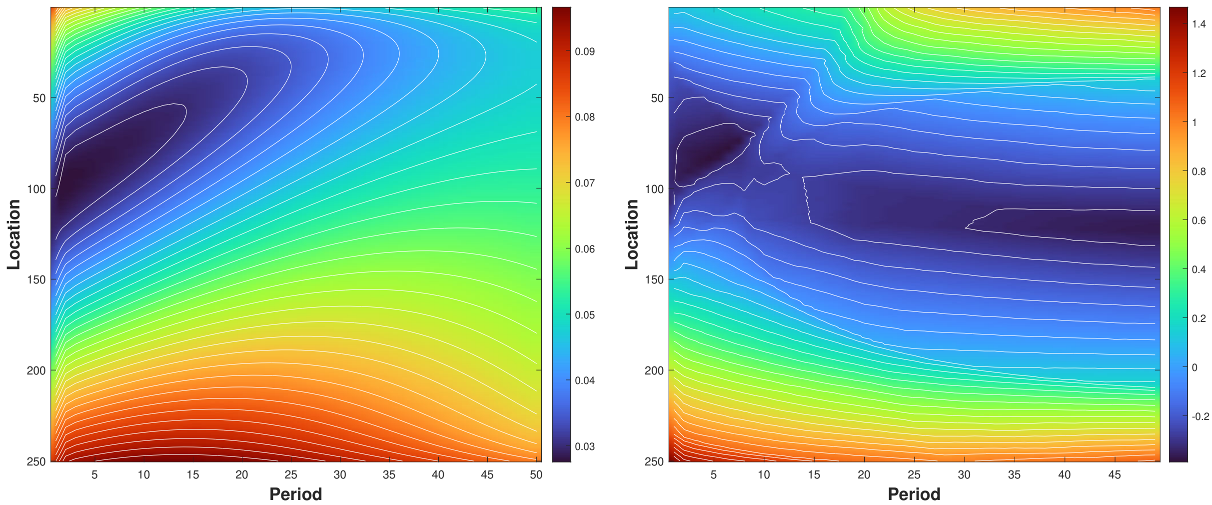


(a) Aggregate Employment Change (b) Variation of Housing Prices

housing prices for different scenarios. When the productivity of manufacturing grows at a higher rate, the structural transformation from manufacturing to services proceeds and it generates more variation of housing prices due to the agglomeration of services. For the high migration costs, I can see a similar pattern of structural transformation in the macroeconomy. However, the spatial variation of housing prices becomes large compared to the baseline since high migration costs prevent individuals from adjusting their locations and agglomerations are reinforced.

I turn to inequality and upward mobility in Figure 10. The left-hand panel 10a shows an increase in income inequality in the left cities due to the rapid structural transformation compared to the baseline. In contrast, the right cities show small income inequality due to the further specialization of tradable services than the baseline. The right-hand panel 11a gives the spatial variation of upward mobility corresponding to Figure 8b. Comparing these two figures, I find that central places exhibit lower upward mobility from the early period. The structural change due to the technological progress of manufacturing leads to specialization of workers in the edge cities and worse off individuals in the central cities in terms of mobility. Intuitively, this suggests the role of technology-driven structural transformation in the declining upward mobility of workers. Next, Figure 11 give these patterns for the case of high migration costs. The left-hand panel 11a shows a similar

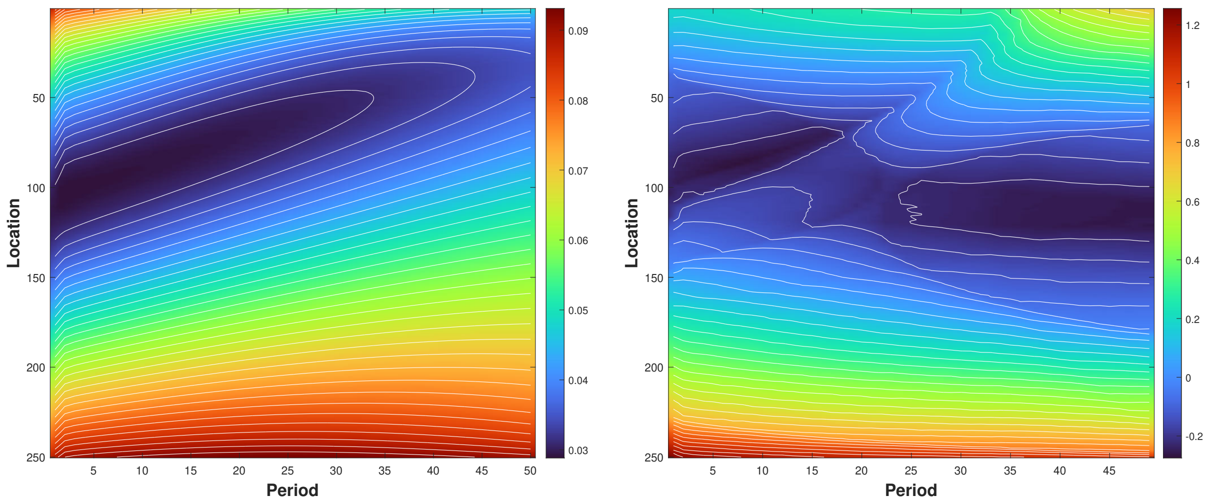
Figure 10: Inequality and Upward Income Mobility When Productivity Growth of Manufacturing



(a) Coefficient of Variation in Income

(b) Upward Mobility

Figure 11: Inequality and Upward Income Mobility When High Migration Cost



(a) Coefficient of Variation in Income

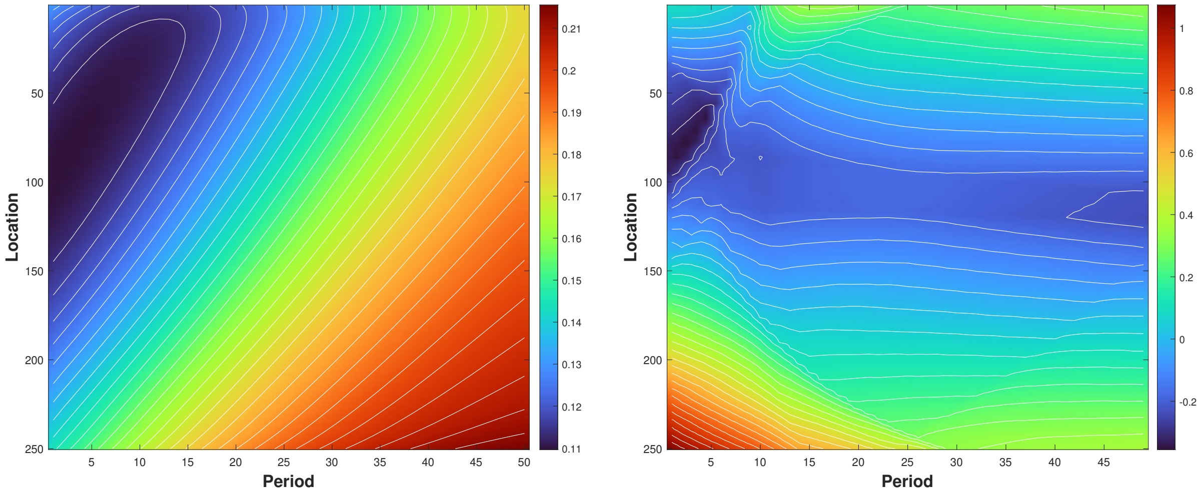
(b) Upward Mobility

pattern of inequality in the local labor market to the baseline results. This implies that the bilateral migration costs have a limited impact on inequality within the city. Nevertheless, the right-hand panel 11b shows that upward mobility is small for most locations relative to baseline when migration is costly. With high migration frictions, workers are unable to leverage geographical mobility, and therefore, workers are less able to climb up the income ladder by moving across cities.

IV.D.II Role of Local Labor Market Exposure

Lastly, I exploit the simple economy to understand the role of local labor market exposure in the sector choice of workers by setting a lower value of η. The parameter controls the limited exposure of individuals to the local labor market as I discussed in Assumption 2. As a contrast to the baseline value of η, I set $\eta = 0.10$. This implies that the effect of the previous generation in the local labor market has less impact on the choice of the sector. Figure 12 give inequality and upward income mobility for the alternative parameter value. First, I see significant income inequality compared to the baseline. All locations show an increase in income inequality over time. When the persistent effect of local labor market exposure is weak, less specificity to

Figure 12: Inequality and Upward Income Mobility When $\eta = 0.10$



(a) Coefficient of Variation in Income

(b) Upward Mobility

sector and location fosters the mobility of workers and it leads to less specialization of workers in equilibrium. Therefore, I see a rise in income inequality within a city and less variation of housing prices (Panel 9b). In the right-hand panel 12b, I see the relatively low intergenerational income mobility. The less specialization and structural transformation lead to a small variation of real income across locations and a small gap in expected return from sector choice between the tradable service sector and non-tradable service sector. Together, the intergenerational income mobility becomes low and shows small geographical variation. Overall, the local labor market exposure impacts inequality and upward mobility by the direct effect in the sector choice of workers and an indirect effect through the specialization of workers in local labor markets.

V 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, I use data and model structure to estimate parameters and obtain the fundamentals in the real economy.

I map the model 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, I consider the construction sector, 9 manufacturing industries, and 8 service industries. The construction sector corresponds to sector 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, I construct the data of employment and industry wage from the County Business Pattern (CBP), the American Community Survey (ACS) and decennial censuses. Through the analysis, I focus on 395 CBSAs where I am able to construct these data for different periods. I measure geographical distances between CBSAs. For each pair of CBSAs, the distance is computed between the reference points for the pair of most populated counties.

Model calibration proceeds in two parts. In subsection V.A, I discuss the parameters in the model. First, I explain the choice of parameters for the demand system and production technology. I set parameters in the non-homothetic demand system $(\alpha_s, \theta_s, \sigma)$, production technology for manufacturing and service sectors (β_{sj}) and technology in development of residential stocks (χ). Second, I discuss the key parameters in trade. I exploit the gravity structure for manufacturing sectors and tradable services and determine the trade elasticity (κ_s). Third, I consider the set of parameters in labor supply. I combine the structure of the model and parameter value of migration elasticity (ϵ) from literature to pin down the industry choice parameters (η, ϕ). Fourth, I discuss the parameter choice for the economies of scale (γ_s) and productivity spillover (ρ).

In subsection V.B, I leverage the structure of the model to back out the fundamentals in the U.S. economy. This procedure is sequential, and therefore I discuss it step by step. I assume that the economy is in the stationary steady state equilibrium in the last period 2010. Then, the structural relationships allow us to derive the fundamentals in the development of residential stocks ($\nu_i, \bar{h}_i$), location fundamentals of amenity, and location and industry 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 Appendix E.

V.A Parameters

I explain the parameters in the baseline analysis. Table 1 reports the summary.

Parameters in Demand and Production. The demand system has three parameters. For the elasticity of substitution between sectors, I set $\sigma = 0.40$ following the macroeconomic literature on structural transformation. This ensures the complementarity between different sectors. I assign the slope of the Engel curve based on the estimation from Comin et al. (2020). In particular, I set different values between two large categories of manufacturing sector and service sector. Namely, θ_s is normalized to 1.0 for the construction sector and manufacturing sector. For service sector, I set θ_s such that $(\theta_s - \sigma)/(1-\sigma) = 1.75$, which is in the middle of estimates from Table I in Comin et al. (2020). In turn, θ_s is equal to 1.375 for service sector. This implies that expenditure share on manufacturing sectors is independent of real income, while expenditure share on service sectors increases in real income. For the rest of the parameters in the demand system, the parameters of demand shift (α_s) are chosen to match the year 2010 expenditure shares in the manufacturing and service sector.

I need input share for each industry: labor input share is β_s, and input from other sectors is β_{sj}. Using the US Bureau of Economic Analysis (BEA) table of input-output accounting, I compute these shares to match the average values during $2011 - 15$. Since I do not consider the international trade of intermediate goods as a baseline, I need to adjust the input-output identity, and the labor share is computed as the share of labor compensation in the adjusted total production values based on the identity. The parameters of input-output linkages are equal to the share of input purchases from other industries. 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. Therefore, the aggregate surplus is a constant share, $1 - \chi = 0.65$, of the total value of structure in every period.

Trade elasticity. The regional trade in the model is the gravity fashion. I parametrize the impediment of trade. The trade costs for non-service industries between two locations are decomposed into an elastic function of geographical distance with elasticity δ, origin-specific friction, and destination-specific friction. Then, I obtain the restricted gravity equation for the value of export from n to i:

$$\ln X^s_{in,t} = \mathbb{D}^s_{i,t} + \mathbb{O}^s_{n,t} - \kappa_s \delta \ln dist_{in} + \varepsilon^s_{in,t} \tag{19}$$

where $\mathbb{D}^s_{i,t}$ factors destination characteristics and $\mathbb{O}^s_{n,t}$ factors characteristics of source locations, respectively. I estimate $\kappa_s\delta$ for the trade of 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 (κ_s) and trade cost elasticity (δ), I assume that $\delta = 0.125 = 1/8$. 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 (κ_s) by manufacturing industries that are in the range of estimates in the literature of international trade (Head and Mayer 2014, Simonovska and Waugh 2014) as well as domestic trade (Gervais and Jensen 2019).

Turning to the service sector, I cannot directly observe the trade flows. Therefore, I rely on the estimation by Anderson et al. (2014). Their estimates can be directly used to my definition of service sectors to pin down the trade elasticity of services. I assume the same value of trade cost elasticity as manufacturing sectors and obtain the different Fréchet shape parameters by service industries. They are within the range of estimates in Gervais and Jensen (2019). See Table E.3 in Online Appendix for numbers.

Table 1: Parameters

Parameter	Source and Comments
1. **Demand**: $\sum_j (\alpha_j c_j)^{(\sigma-1)/\sigma} \mathbb{U}^s_{n,t}(\omega)^{(\theta_j-\sigma)/\sigma} = 1$	
$\sigma = 0.40$	Elasticity of substitution between industries
$\theta_M = 1.00, \quad \theta_S = 1.375$	Sector specific non-homotheticity; Comin et al. (2020)
	θ_M for all industries in manufacturing; θ_S for all industries in service
$\alpha_M = 3.00, \quad \alpha_S = 0.1, \quad \alpha_0 = 0.25$	Sector level demand shifter
	Matched to expenditure share ratio between service and manufacturing sector
2. **Production**: $\Xi^s_{nt} = (w^s_{nt})^{\beta_s} \prod_{j\in\mathcal{K}\backslash 0} (p^j_{nt})^{\beta_{sj}}$, $h_{i,t} = \nu_i \left(\ell^0_{i,t}\right)^{\chi} \left((1-\bar{h}_i) h_{i,t-1}\right)^{1-\chi}$	
β_s, β_{sj}	Input share; BEA table of input-output accounting
$\chi = 0.35$	Labor share in housing construction; BEA table for construction sector
3. **Productivity**: $F_s(\varphi) = \exp(-\varphi^{-\kappa_s})$, $Z^s_{i,t} = A^s_{i,t}\left(\sum_n L^s_{in,t} Z^s_{n,t-1}\right)^{\rho} (L^s_{i,t})^{\gamma_s}$	
κ_s	Trade elasticity from gravity estimates using CFS for manufacturing;
	Anderson et al. (2014) for services; see Table E.1 in Online Appendix
$\rho = 0.0284$	Spillover in productivity across space; internal estimation
γ_s	Local externalities; upper bound of uniqueness condition
	see Table E.3 in Online Appendix
4. **Workers' Choice**: $G(v) = \exp(-\sum_n v_n^{-\epsilon})$, $\mathcal{O}(j^k_i, L^k_{i,t}) = \frac{1}{\zeta_k} \ln\left(\frac{1}{1-j^k_i}\right)(L^k_{i,t})^{-\eta}$, $F(z) = 1 - z^{-\phi}$	
$\epsilon = 1.50$	Migration elasticity; Fajgelbaum et al. (2019)
$\phi = 2.50$	Variation of taste shocks; estimation from migration pattern
$\eta = 0.80$	Local labor market exposure effect; estimation from migration pattern
5. **Spatial frictions**: $D_{in,t} = (dist_{in})^{\widetilde{\delta}} M_{i,t}$, $\tau_{in,t} = (dist_{in})^{\delta}$	
$\delta = 0.125$	Trade cost elasticity; Eaton and Kortum (2002)
$\widetilde{\delta} = 0.50$	Migration cost elasticity from gravity estimates

Note: This table reports parameters in calibration and quantitative analysis.

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 migration elasticity of workers is ϵ. This is the shape parameter of Fréchet distribution of the idiosyncratic shocks in location choice. Therefore, the parameter captures the elasticity of labor allocation across different locations with respect to real income: $\epsilon = \frac{\partial \ln\left(L^s_{i,t}/L^s_{n,t}\right)}{\partial \ln\left(\mathcal{W}^s_{i,t}/\mathcal{W}^s_{n,t}\right)}$. Following Fajgelbaum et al. (2019), I set $\epsilon = 1.5$. Next, I consider the migration costs. Suppose that the bilateral migration cost is decomposed into an elastic function of bilateral distance and destination characteristics. In particular, I parametrize $D_{in,t} = (dist_{in})^{\widetilde{\delta}} M_{i,t}$ for migration cost from n to i, where $dist_{in}$ is geographical distance, $\widetilde{\delta}$ is positive constant and $M_{i,t}$ is time varying destination characteristics. Under this parametrization, the model derives the gravity equation of labor mobility across space conditional on sector choice:

$$\ln L^s_{in,t} = \mathbb{W}^s_{i,t} - \epsilon\widetilde{\delta} \ln dist_{in} + \mathbb{H}^s_{n,t} \tag{20}$$

where

$$\mathbb{W}^s_{i,t} = \epsilon \ln \mathcal{W}^s_{i,t} - \epsilon \ln M_{i,t}, \quad \mathbb{H}^s_{n,t} = \epsilon \ln \varsigma^s_{n,t} - \epsilon \ln \bar{U}^s_{n,t} + \ln L_{n,t-1}$$

contain source location and industry characteristics, and destination and industry characteristics, respectively. To estimate $\widetilde{\delta}$, I use American Community Survey (ACS) 5 year sample data between $2006-10$ and $2011-15$. In the sample, the ACS data allows me to identify the current location county, previous county and industry of the worker. I extract workers in sectors of my analysis and map their locations to the CBSA level. Then, I focus on workers who moved between different CBSAs in the sample and estimate the gravity equations. Based on the estimates during different sample periods, $2006-10$, $2011-15$ and $2006-10$, I set $\widetilde{\delta} = 0.50$.[24]

Once I have the migration elasticity and bilateral term in migration cost, I leverage the structural equations for labor mobility to calibrate the other two parameters in the choice of individuals (η and ϕ). Given the parameters (ϵ, $\widetilde{\delta}$), the model allows me to characterize the mobility of workers in equilibrium. In particular, for each pair of values (ϕ, η), I uniquely determine the set of endogenous characteristics that rationalize the observed change in the distribution of workers. In turn, I can compute predicted migration flow, $\widehat{L}_{in,t}$. Therefore, I can define the moment conditions that argue the difference between the observed pattern of labor mobility ($L^{Data}_{in,t}$) and the predicted one in the model ($\widehat{L}_{in,t}$) are not systematically correlated to the bilateral distances between source and destination in the same range of distances. As an observation of labor mobility, I exploit Internal Revenue Service (IRS) county-to-county migration data and aggregate them to the CBSA pairs for two time periods, $1990-2000$ and $2000-10$. Comparing the pattern of labor mobility between data and prediction, I obtain the estimated value of two parameters: $\phi = 2.50$ and $\eta = 0.80$.

Parameters in productivity. The parameter in the productivity is γ_s controls the strength of the externalities in production. I assign the value of γ_s 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_s is not too large to avoid the black hole equilibria in which production of intermediate good is concentrated in one location. Since the long-run equilibrium in history does not show such a black hole equilibrium, I use the condition to set γ_s. As I discussed in Section III, one of the condition that is related to the uniqueness of the dynamic equilibrium conditional on the initial state is given by $\gamma_s \leq \frac{\theta_s - \sigma}{\kappa_s + (1-\sigma)}\left(1 + \frac{1}{\epsilon}\right)$. 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, I allow $\rho \neq 0$. If I introduce the spillover in productivity across space through migration of workers, it leads to further agglomeration forces in the steady state since favorable locations attract workers while the remoted places lose. Therefore, I take the conservative values that satisfy the condition with additional restriction $\epsilon \to \infty$. 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 $\gamma_s = \frac{\theta_s - \sigma}{\kappa_s + (1-\sigma)}$. For comparison to the existing values in empirical studies, I also refer values in Combes et al. (2012) and Bartelme et al. (2021) in Appendix E.2.5. It is worth emphasizing that I assume that $\chi = 1$ to derive the condition. If $\chi < 1$, the supply of residential stocks becomes less elastic and congestion force arises. Therefore, setting $\chi = 1$ keeps the conservative value for purpose. Lastly, for the parameter of spatial spillover (ρ), I discuss it in the next subsection along with the inversion of productivity.

[24] 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.

V.B Calibration of Fundamentals

Next, I solve the model for the fundamentals of the economy conditional on the information about the local labor markets. The inversion of the fundamental productivity ($A^s_{i,t}$), fundamental location characteristics ($B^s_{i,t}$, $M_{i,t}$, ν_i and $\bar{h}_i$) and fundamental sectoral parameter ($\zeta_{s,t}$) proceeds in two steps. In the first step, I assume that the economy is in the steady state level in 2010 and compute the time-invariant location characteristics in the development of residential stock (ν_i and $\bar{h}_i$) by using the information of price of housing. Then, I use the system of equations in the equilibrium to back out the overall productivity (Z^s_i) and attractiveness of locations that combine amenities (B^s_i) and migration friction (M_i). Once I obtain the overall productivity, I compute the exogenous part of productivity (A^s_i) along with the estimation of parameter ρ. In the next step, I solve the model for the time-varying fundamentals. I match the dynamic equilibrium and observation of wage and employment for the inversion of the path of exogenous part of productivity ($A^s_{i,t}$), amenities ($B^s_{i,t}$), migration frictions ($M_{i,t}$) and sectoral shifter ($\zeta_{s,t}$). The whole process is sequential, so I explain the procedure by step.

Efficiency of development of residential stock. In the steady state, (10) implies that

$$\widetilde{\nu}_i \equiv \nu_i(1-\bar{h}_i)^{1-\chi} = \exp\left(\chi(-\ln\chi + \ln w^0_i - \ln p^0_i)\right) \tag{21}$$

where I have equilibrium wage (w^0_i) and housing price (p^0_i). Data for the housing price comes from Federal Housing Finance Agency (FHFA). I exploit the Housing Price Index (HPI) of all-transactions index across CBSAs for 2010. The location characteristics $\widetilde{\nu}_i$ combines efficiency of development (ν_i) and persistency of residential stocks ($\bar{h}_i$). In Online Appendix E.3, I show the spatial distribution of efficiency of development across CBSAs inverted in the model. Intuitively, CBSAs with large values $\widetilde{\nu}_i$ implies that there is a persistency of residential stock and higher efficiency of construction. In equilibrium, the geographical differences in $\{\widetilde{\nu}_i\}$ affect the spatial variation of housing supply and price changes.

Productivity. I solve for the overall productivity in location i and sector s, Z^s_i in the steady state. The zero profit condition of producers (9) implies:

$$\Gamma_s^{\kappa_s}\left(p^s_i\right)^{-\kappa_s} = \sum_n \left(\left(\widetilde{\tau}^s_{in}\right)^{-\kappa_s}\left(Z^s_n\right)^{\kappa_s}\left[\left(w^s_n\right)^{\beta_s}\prod_j\left(p^j_n\right)^{\beta_{sj}}\right]^{-\kappa_s}\right) \tag{22}$$

where $\widetilde{\tau}^s_{in} \equiv (dist_{in})^{\delta}$ is bilateral trade costs. Given productivity and wages, solving this allows me to characterize the equilibrium prices. The set of parameters ($\kappa_s, \delta, \beta_s, \beta_{sj}$) are given in the previous discussion. Turning to the demand system, I solve (2) for the non-homothetic aggregate price index:

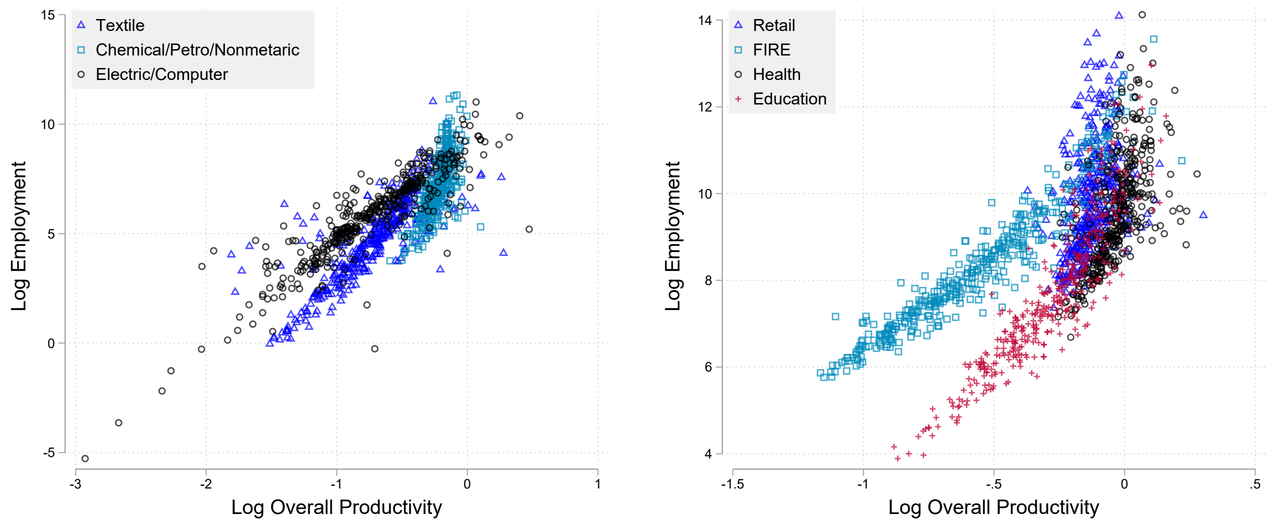
$$\left(\mathcal{P}^s_i\right)^{1-\sigma} = \sum_j \alpha_j^{\sigma-1}\left(p^j_i\right)^{1-\sigma}\left(\frac{W^s_i}{\mathcal{P}^s_i}\right)^{\theta_j-1} \tag{23}$$

where income of workers (W^s_i) is constructed from the wage and employment. Given the parameters of preference ($\sigma, \theta_s, \alpha_s$) and $\theta_s \geq \sigma$ and $\sigma \in (0,1)$, I obtain the unique matrix of price index $\{\mathcal{P}^s_i\}$ solving (23). Then, I use the labor market clearing condition. (15) implies:

$$Z^s_i = \left(\frac{w^s_i L^s_i}{\beta_s}\right)^{\frac{1}{\kappa_s}}\left(\left(w^s_i\right)^{\beta_s}\prod_j\left(p^j_i\right)^{\beta_{sj}}\right)\left(\sum_n\left(\widetilde{\tau}^s_{ni}p^s_n\right)^{-\kappa_s}\sum_j\left[\beta_{js}\frac{w^j_n L^j_n}{\beta_j} + \alpha_s^{\sigma-1}\left(p^s_n\right)^{1-\sigma}\left(\mathcal{P}^j_n\right)^{\sigma}\left(\frac{W^j_n}{\mathcal{P}^j_n}\right)^{\theta_s}L^j_n\right]\right)^{-\frac{1}{\kappa_s}} \tag{24}$$

Combining (22), (23) and (24) allows inversion of productivity $\{Z_i^s\}$ that is consistent with the observation to be the equilibrium. Figure 13 shows the relationship between overall productivity (Z_i^s) implied by the

Figure 13: Productivity and Employment for CBSAs



(a) Manufacturing industries

(b) Service industries

Note: These figures show log scale of overall productivity (Z_i^s) and log scale of employment for particular industries in 2010.

model and employment (L_i^s) in 2010. Each mark shows CBSA in the analysis. The left-hand panel 13a shows the relationship for three industries in the manufacturing sector: textile, chemical/petro/coal products and electric/computer industry. I find a larger variation of overall productivity for the electric/computer industry than the other two industries. This is consistent with the dispersion of workers in the industry over space. The right-hand panel 13b presents four industries in the service sector: retail, finance, insurance and real estate (FIRE), health and education/legal services. FIRE and education services exhibit relatively large variation across CBSAs in overall productivity compared to retail and health.

Location amenities and industry taste. As a next step, I use the model structure for the inversion of amenities and location characteristics in the migration frictions – location attractiveness. I solve for the steady state level of them in order to use the pattern of labor mobility in the next step. In the steady state, amenities ($B_{i,t}^s$) and migration barrier ($M_{i,t}$) are constant. The two location fundamentals ($\{B_i^s\}$, $\{M_i\}$) decide the exogenous gains for workers who choose the destination, and it is impossible to isolate them. In addition, there is another fundamental in the industry choice. The constant parameters $\{\zeta_s\}$ capture the taste shifter of workers by sector. I let $\Omega_i^s \equiv (B_i^s/M_i)\zeta_s^{1/\phi}$ that conflates these fundamentals. Then, (4) implies that adjusted average utility of a worker in location n in sector s is:

$$\bar{\mathbb{U}}_n^s = \left(\sum_i \left[\Omega_i^s \widetilde{D}_{in} \frac{W_i^s}{\mathcal{P}_i^s} \right]^{\epsilon} \right)^{1/\epsilon} = \zeta_s^{1/\phi} \bar{U}_n^s \tag{25}$$

where $\widetilde{D}_{in} \equiv dist_{in}^{-\widetilde{\delta}}$ is the inverse of bilateral migration frictions. Using this, I compute the inferred probability of location choice for workers in sector s ($\{\lambda_{in|s}\}$) and the probability of industry choices ($\{\varsigma_n^s\}$). Then, I use the labor mobility condition (12) for computing the attractiveness of location i and sector s with implementing the aggregate price index derived in (23). In this step of inversion, I also compute the predicted labor mobility ($\{\widehat{L}_{in}^s\}$) in the steady state and use this information in the next step.

Fundamental Productivity. I proceed to the inversion of fundamental productivity and calibration of parameter ρ. In the steady state, the exogenous fundamental productivity satisfies:

$$\ln A_i^s = \ln Z_i^s - \rho \ln \left(\sum_n L_{in}^s Z_n^s \right) - \gamma_s \ln L_i^s \tag{26}$$

I implement the productivity ($\{Z_i^s\}$) derived in the previous step and the labor mobility ($\{\widehat{L}_{in}^s\}$) into this. Given the employment data ($\{L_i^s\}$) and parameter values ($\{\gamma_s\}$), I am able to compute the fundamental productivity for each value of ρ. To estimate ρ, I consider the following moment conditions:

$$\mathbb{E}\left[\left(\ln A_i^s - \frac{1}{N} \sum_n \ln A_n^s - \frac{1}{S} \sum_k \ln A_i^k \right) \times \mathbb{I}_g \right] = 0, \quad g \in \mathbb{G}_0, \mathbb{G}_1, \cdots, \mathbb{G}_P \tag{27}$$

where $\mathbb{I}_g$ is an indicator that the location i and sector s is in the group of g. The group is defined by the labor market potential for each location and sector. Namely, for location i and sector s, I compute the measure $\sum_{n \neq i} \left(dist_{ni} \right)^{-\epsilon \delta_{\mathrm{M}}} L_n^s$, and I order locations and sectors by the measures. Based on the order, I use 20 groups defined by 5 percentile of the measure. The moment condition assumes that the location and industry specific fundamental productivity after eliminating the averages is not systematically related to the labor market access since the spatial dependence of productivity is captured by the second term in (26). Therefore, I use (27) and search parameter ρ that minimizes the distances of the moment conditions. In result, I obtain $\widehat{\rho} = 0.0284$ that is reported in Table 1.

Dynamics of Fundamentals. Once I have characterized the fundamentals in the steady state equilibrium, I compute the path of the time-variant environment of the economy conditional on the information about the local labor market. Specifically, I compute change of fundamental productivity and location attractiveness ($\{\mathrm{d} \ln A_{i,t}^s\}$, $\{\mathrm{d} \ln M_{i,t}\}$) for periods: $2000 - 2010$, $1990 - 2000$ and $1980 - 1990$. I suppose that the economy reaches the steady state equilibrium in 2010, and I backcast the change of these fundamentals in the past. I follow four steps as in the previous procedure for the steady state equilibrium.

First, I compute the residential stock and their prices in the past conditional on the current observations. The production function of developers (10) implies the previous residential stocks:

$$\ln H_{i,t-1} = \frac{1}{1-\chi} \Big(\ln H_{i,t} - \ln \widetilde{\nu}_i - \chi \ln L_{i,t} \Big) \tag{28}$$

and market clearing condition leads to the price of residential stocks:

$$\ln p_{i,t-1}^0 = - \ln \chi + \ln w_{i,t-1}^0 + \ln L_{i,t-1}^0 - \ln H_{i,t-1} \tag{29}$$

I implement parameter in production technology of residential structure (χ), observed wage and employment in the construction sector and location fundamentals ($\{\widetilde{\nu}_i\}$) to obtain the path of ($\{p_{i,t-1}^0\}$, $\{H_{i,t-1}\}$, $\{R_{i,t-1}\}$) in the dynamic equilibrium that are not directly observable. In HPI, I have limited data of prices for CBSAs in 1990 and 1980 and therefore I can gauge the model specification in (28) and (29). In Online Appendix E.3.2, I show the comparison between prices across CBSAs predicted by the model and the limited data for 1980 and 1990. Second, I compute the path of productivity $\mathrm{d} \ln Z_{i,t}^s$, such that wage and employment in the past are consistent with equilibrium. I guess the productivity in the past ($\mathrm{d} \ln Z_{i,t}^s$) and compute the change of prices and trade patterns. I solve the static equation (23) for the aggregate price index, and I use the market clearing condition (24) to update the productivity change. Next, I use the forward equations in the model for computing the path of location attractiveness. The labor mobility condition (12) implies that the adjusted attractiveness for location i and sector s satisfies:

$$\Omega_{i,t}^{s} = \left(\frac{1}{L_{i,t}^{s}} \sum_{n} \left(\frac{\widetilde{D}_{in}}{\mathbb{U}_{n,t}^{s}} \left[\frac{W_{i,t}^{s}}{\mathcal{P}_{i,t}^{s}} \right] \right)^{\epsilon} \frac{\left(L_{n,t-1}^{s}\right)^{\eta} \left(\mathbb{U}_{n,t}^{s}\right)^{\phi}}{\sum_{j} \left(L_{n,t-1}^{j}\right)^{\eta} \left(\mathbb{U}_{n,t}^{j}\right)^{\phi}} L_{n,t-1} \right)^{-1/\epsilon} \tag{30}$$

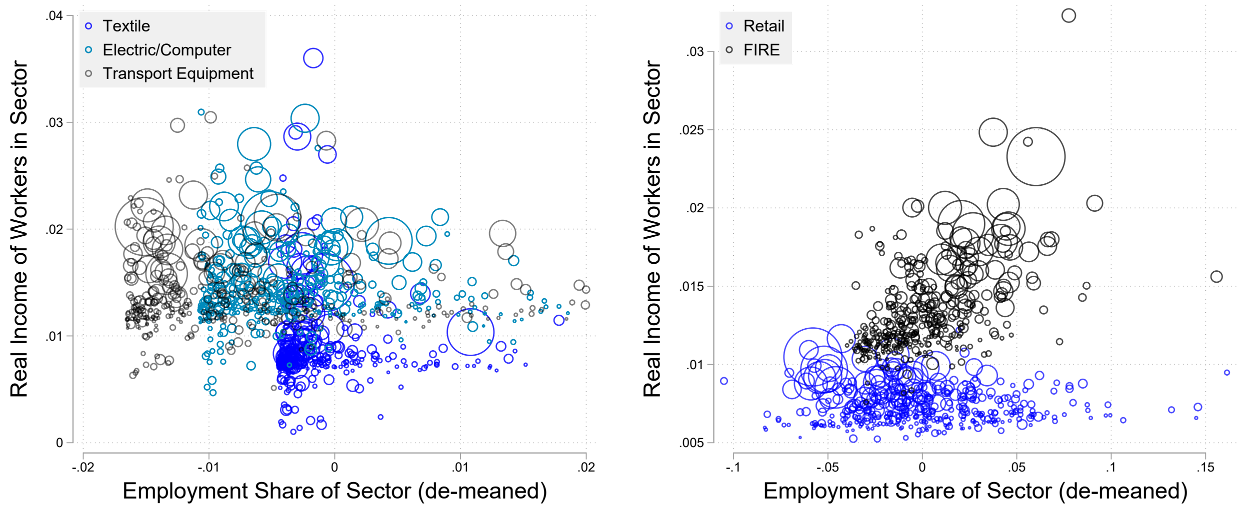
where $\mathbb{U}_{n,t}^{s}$ is derived for each generation as in (25). Conditional on the observation about employment ($\{L_{i,t}^{s}\}$) and income and aggregate price index constructed by the model, I obtain the location and sector specific adjusted amenities ($\{\Omega_{i,t}^{s}\}$) in each period. Then, I am able to compute the two probabilities of workers' choice ($\{\lambda_{in|s,t}\}$, $\{\varsigma_{n,t}^{s}\}$) predicted by the model. Lastly, I compute the development of fundamental productivity in the analogous way to (26). Given the overall productivity of two consecutive periods ($\{Z_{i,t}^{s}\}$, $\{Z_{i,t-1}^{s}\}$), employment ($\{L_{i,t}^{s}\}$) and labor mobility ($\{L_{in,t}^{s}\}$), I compute fundamental productivity ($\{A_{i,t}^{s}\}$) that is consistent with the dynamic equilibrium. For the initial period, I set $A_{i,t}^{s} = Z_{i,t}^{s}$ in 1980.

VI Quantitative Analysis

Having an inversion of the model to obtain the fundamentals in the economy and estimated parameters, I assess the role of these fundamentals and analyze the dynamics of TFP, welfare and inequality across CBSAs in the U.S. economy. I first discuss the role of industry and location specific amenities for workers' distribution. As I discussed in the previous section, in the model calibration, I only identify the amenities adjusted with location-specific migration barriers and sector-specific taste parameters. The variation of amenities plays an important role in determining the evolution of workers' location in the structural transformation. Then, I discuss the TFP changes. I derive the measured TFP predicted by the model and discuss the industry level and aggregate TFP at sector level: manufacturing and service. Next, I discuss the welfare differences of individuals between two generations and how they are different across locations. Following theoretical results in Proposition 3, I present the different margins in welfare dynamics. Lastly, I explain how the measure of intergenerational income mobility derived in the model shows spatial variation and investigate its relationship to the underlying mechanisms in the general equilibrium.

Amenities. As I discussed in the previous section, the amenities in each local labor market, $\Omega_{i,t}^{s}$ is obtained by exploiting the model structure. I first discuss their role in the pattern of structural change. Figure 14 shows the relationship between 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, $\mathcal{W}_{i,t}^{s}$, derived in the model. I compute the real income 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 14a displays three industries among the manufacturing sector. The employment share exhibits large variation relative to real income, and the pattern is different across industries. This confirms that there exist industry-specific amenities for workers. In the right-hand panel 14b, I show 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 the industry and location specific amenities for workers' location choices and such amenities are crucial to explaining the spatial variation of employment shifts.

Figure 14: 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.

In Online Appendix F, I also confirm the relationship between the average level of amenities and the size of employment in CBSA. The relationship is stable over time, which suggests the importance of location fundamentals for the persistency in the aggregate size of employment in CBSA. Furthermore, in Online Appendix F.1, I report the geographical distribution of the average value of amenities, CBSAs with the highest average amenities and correlation between average amenities and some observed characteristics in CBSA.

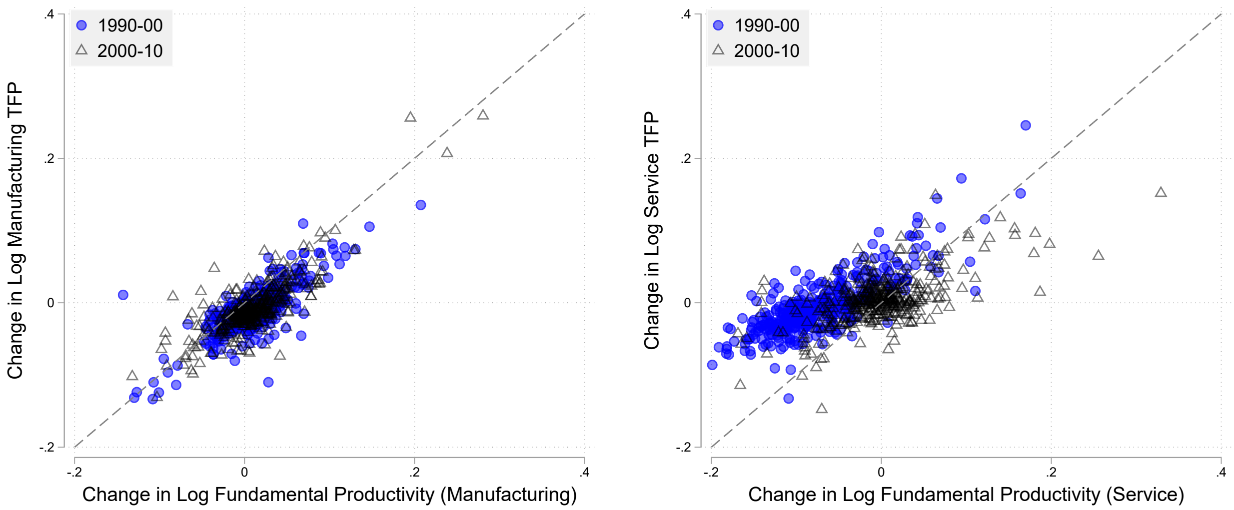
Productivity. As I discussed in Section IV and proposition 2, I am able to compute measured TFP for each CBSA and industry given overall productivity ($\{Z^s_{i,t}\}$) and trade probabilities ($\{\pi^s_{ii,t}\}$). Using the equilibrium relationships, I compute TFP for each period. I find distinctive dynamics of the spatial distribution of measured TFP by industry. For instance, for the electric and computer industry, I can identify an increase in the spatial variation of TFP and the development of clusters in California and large metropolitan areas on the East coast. I also see the different evolution of TFP for FIRE. In the initial period 1980, the variation of TFP across CBSAs is small and TFP is relatively low. However, over time, I see a remarkable increase in its level and variation. The industry has seen a significant development on the East coast (New York metropolitan area) and large cities that are the hub of the financial market in each region (Chicago, Dallas, Atlanta and Nashville) from 1980 to 1990. Then, these clusters show persistent development over time, while some other inland cities also have seen a rise in FIRE. These spatial distributions are in Online Appendix F.1. The developments of TFP over time are the combination of exogenous productivity change and endogenous spillovers in theory. To see the source of geographical variation and its pattern, in Online Appendix F.1, I additionally report the spatial variation of fundamental productivity and TFP across CBSAs for 17 industries in each period. I find a significant variation in the fundamental productivity for the services sector, leading to the variation of TFP along with the structural transformation.

Having measured TFP of each industry, I compute the aggregate TFP for the sector level: manufacturing and services sector. Namely, for sector K, I compute:

$$\delta^K_{i,t} = \sum_{s\in K} \frac{X^s_{i,t}}{\sum_{j\in K} X^j_{i,t}} \delta^s_{i,t} \tag{31}$$

where $\delta_{i,t}^{s}$ is measured TFP of industry s in location i for period t and $X_{i,t}^{s}$ is value of output of the industry. K is the set of industries in aggregated sectors. In an analogous way, I can compute aggregated fundamental productivity. Figure 15 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.

Figure 15: 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 ($\mathrm{d}\ln A_{i,t}^{K}$) and the change in log of TFP for aggregate sector ($\mathrm{d}\ln \delta_{i,t}^{K}$).

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.

Welfare. Next, I quantitatively evaluate the welfare dynamics I discussed in Proposition 3. I find a large variety of welfare effects across CBSAs.[25] In sum, the welfare differences between generation t and $t-1$ can be decomposed into three different terms:

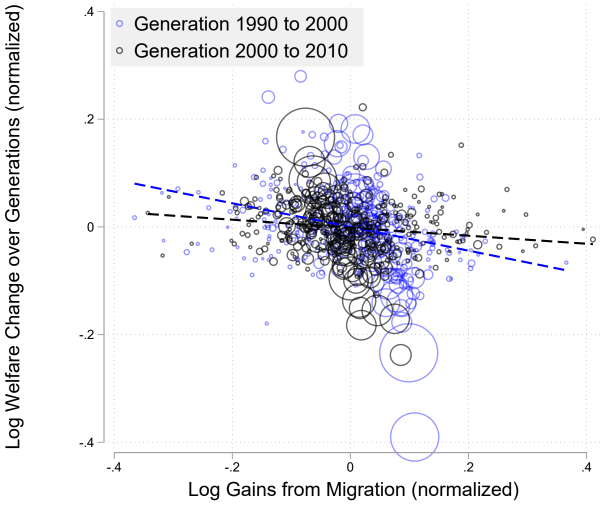
$$\dot{V}_{i,t} = \underbrace{GM_{i,t}}_{\prod_s \dot{\lambda}_{ii|s,t}^{-1/\epsilon}} \times \underbrace{GJO_{i,t}}_{\prod_s \left(\dot{\varsigma}_{i,t}^{s}\right)^{-1/\phi} \left(\dot{L}_{i,t-1}^{s}\right)^{\eta/\phi}} \times GC_{i,t} \tag{32}$$

where $GM_{i,t}$ is gains from labor mobility across space, $GJO_{i,t}$ is gains from job opportunities in the local labor market and $GC_{i,t}$ is local gains from consumption and amenities. Figure 16 presents this relationship for U.S. CBSAs.

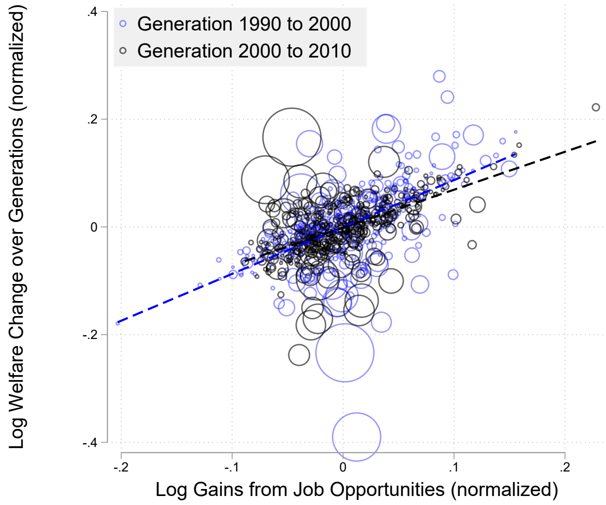
In the first panel (a), higher gains from migration are associated with small welfare differences. The logic is clear. Conditional on industry choice and growth of real income, an increase in the probability of staying in the original location requires higher welfare gains for individuals who stay in 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, specialization of workers into a particular

[25] See Online Appendix F for the map of its spatial pattern.

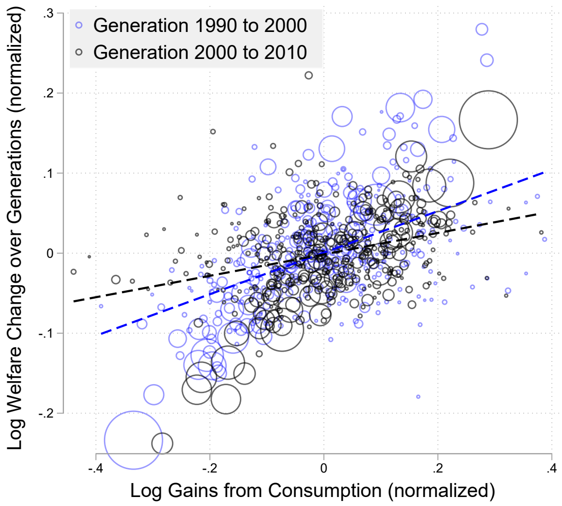
Figure 16: Welfare Differences



(a) Migration



(b) Job opportunity



(c) Consumption

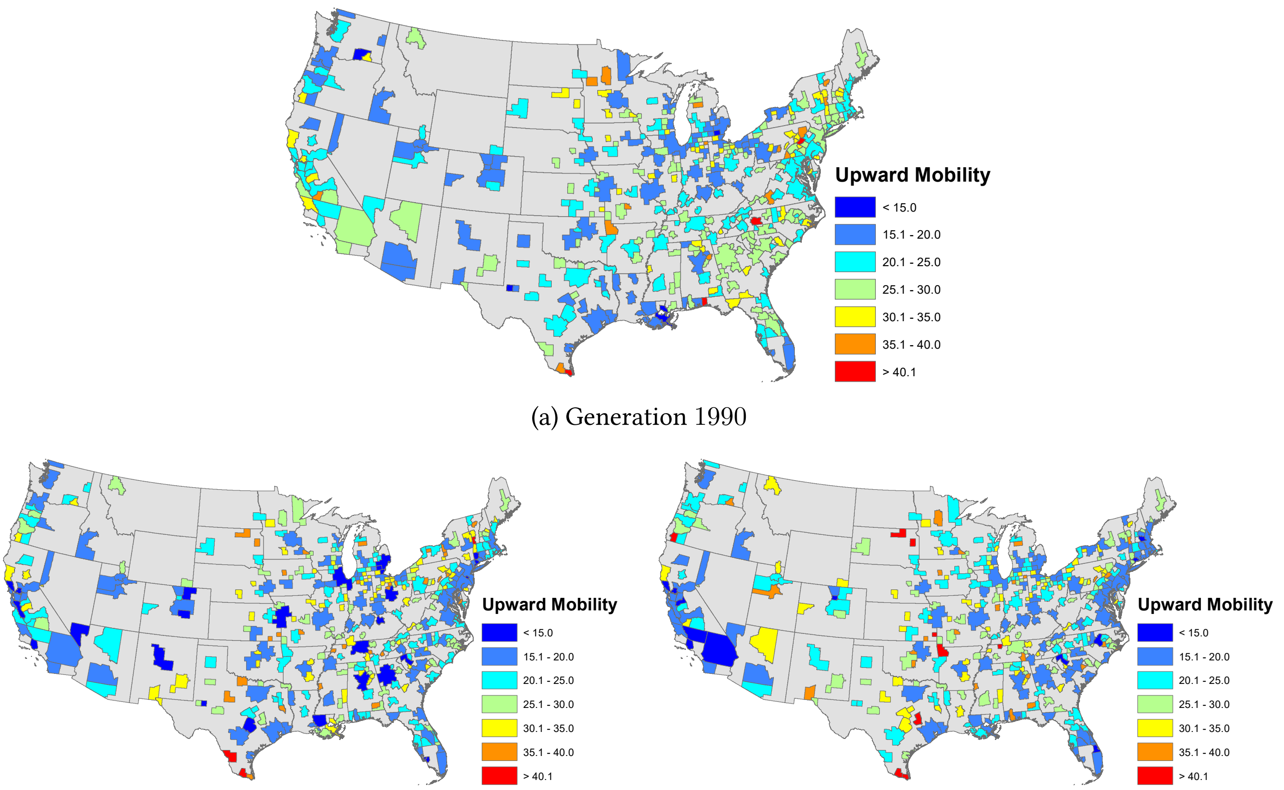
Note: These figures show the different margins in welfare differences for CBSAs. Each circle represents the employment size of CBSA in the baseline year (i.e., employment size in 1990 for the blue circle). All variables are normalized by their means.

industry of 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 persistency in the role of local labor market adjustment. These three margins are quantitatively consistent with the theoretical implications.

Inequality. My final objectives in this section are workers inequality and upward income mobility. For the inequality, following the discussion in Proposition 6, I use the coefficient of variation in income within CBSA as a measure of income inequality. For the intergenerational income mobility, I compute

$$\widetilde{\mathcal{M}}_{i,t+1} = \frac{\mathcal{M}_{i,t+1}}{\bar{\mathcal{M}}_{t+1}} \times 25 \tag{33}$$

Figure 17: Geography of Upward Mobility



(a) Generation 1990

(b) Generation 2000

(c) Generation 2010

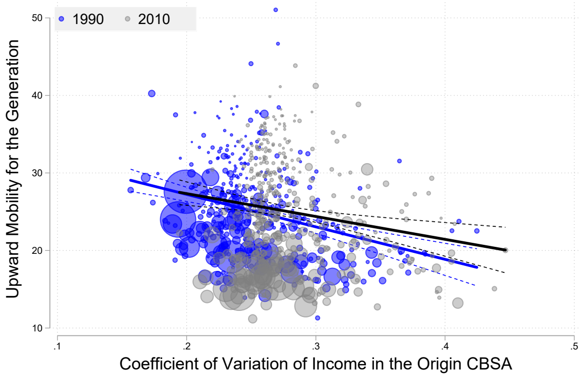
where $\mathcal{M}_{i,t+1}$ is given in Proposition 7 and $\bar{\mathcal{M}}_{t+1}$ is average of $\mathcal{M}_{i,t+1}$ in the economy. Intuitively, this measure gives an expected rank of individuals in CBSA i when their previous generations are in the 25 percentile in the income distribution in the economy.[26] First, my interests are the variation of upward mobility across space. Figure 17 display the measure for different generations. I find a considerable variation of 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, I consider the relation of upward mobility to the underlying mechanisms in equilibrium. Following the discussion in Section IV.C, the measure of upward mobility can be written as:

$$\widetilde{M}_{i,t+1} \propto \sum_{s\in\mathcal{K}} \underbrace{LL^s_{i,t+1}}_{\frac{\mathcal{Q}^s_{i,t}}{\sum_k f^k_{i,t}\mathcal{Q}^k_{i,t}}\frac{\mathcal{Q}^s_{i,t+1}}{\mathcal{Q}^s_{i,t}}} \times \underbrace{ISM^s_{i,t+1}}_{\varsigma^s_{i,t+1}} \times \underbrace{GLM^s_{i,t+1}}_{\sum_n \lambda_{ni|s,t+1}\mathcal{Q}^s_{n,t+1}/\mathcal{Q}^s_{i,t+1}} \tag{34}$$

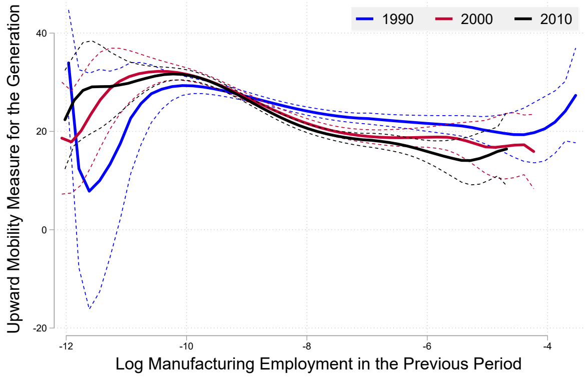
where $LL^s_{i,t+1}$ captures the inequality in the local labor market in period t and local economic growth, $ISM_{i,t+1}$ is patterns of industry choice and $GM^s_{i,t+1}$ is the geographical labor mobility. I can quantify each margin in the model. Figure 18 present these margins. The first panel (a) displays the relationship between upward mobility and local inequality for two generations. The vertical axis is the upward mobility measures for generation 1990 and 2010, and the horizontal axis is inequality in CBSA in 1980 and 2000, respectively. I find the 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. In my model, this arises from the spe-

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

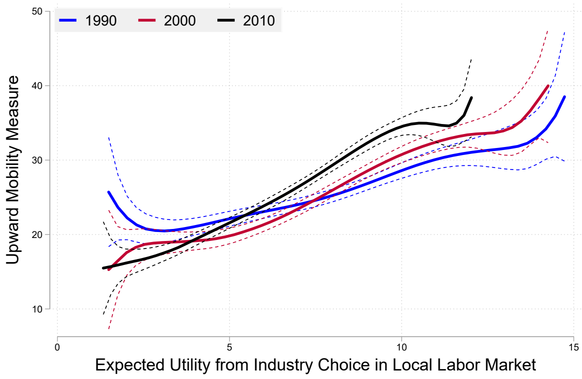
Figure 18: Intergenerational Income Mobility



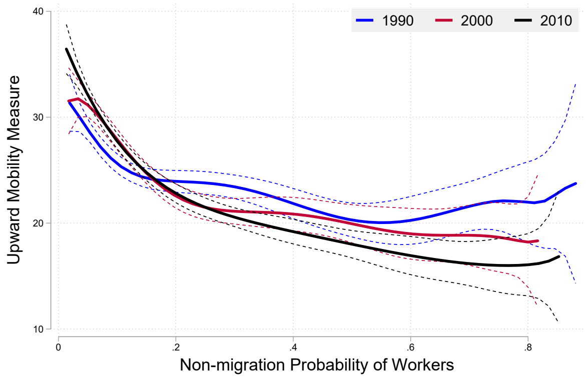
(a) Local inequality



(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. In panel (a), I show the relationship between the measure of upward income mobility for generation 1990 and 2000 to the inequality in the local labor market in period 1980 and 1990 measured by the coefficient of variation. Each marker shows CBSA and blue (black) solid line is fitted line, and dash lines are 95% confidence intervals. In panels (b), (c) and (d), I report the polynomial fitted line for CBSAs. Dash lines are 95% confidence intervals. In panel (b), I show the relationship between 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.

cialization 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. As seen in Figure 2, CBSAs of large employment size in the manufacturing sector exhibited structural transformation to services. Therefore, panel (b) implies that structural transformation lowers the upward mobility of individuals. This accounts for the part of $LL^s_{i,t+1}$. In third panel (c), I consider the land of opportunities for individuals that are related to the intersectoral mobility ($ISM^s_{i,t+1}$). 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 of land of opportunities drives an increase in the spatial variation of upward mobility. The last panel (d) describe the role of labor mobility across CBSAs that is related to $GLM^s_{i,t+1}$. Intuitively, low mobility of workers on geography predicts less possibility to climb up the location ladder *ceteris paribus*. This panel shows the probability of non-migration for individuals from the CBSAs in the horizontal axis. 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.

I have presented the calibrated results for the U.S. CBSAs and quantitative analysis for the general equilibrium implications for measured TFP, workers' welfare, inequality and intergenerational income inequality. My quantitative analysis reveals the underlying mechanisms to create their spatial variation and dynamics. In the next section, I perform counterfactual exercises to understand the contribution of these mechanisms when there are shocks in the fundamentals.

VII Counterfactual Experiments

Armed with the data and parameters calibrated above, I undertake counterfactual experiments to understand the quantitative impact of the development of fundamental productivity and amenities in shaping the variation of structural transformation, TFP growth, welfare and intergenerational income mobility. As I discussed in the calibration, I obtain the trajectory of fundamental productivity ($A^s_{i,t}$) in each CBSA and industry and fundamental amenities ($\Omega^s_{i,t}$) that conflates location and industry specific amenities for workers ($B^s_{i,t}$), migration barrier to CBSA ($M_{i,t}$) and sector specific taste parameters (ζ_s). In the quantitative analysis in the previous section, I discussed the importance of these fundamentals to explain the spatial heterogeneity of workers' location choices and industry choices. The changes in workers' mobility across locations and industries determine their welfare gains relative to the previous generation and their position on the income ladder. My objective of undertaking counterfactuals is understanding the quantitative impact in the dynamic equilibrium. Shocks to fundamental productivity and amenities are salient in shaping individual consequences. Consider the sector level negative shock to the productivity in any particular period. The standard mechanisms are the following: it directly lowers TFP and overall productivity and lowers labor demand and wage, and workers are less likely to sort into the sector, and lower labor supply counteracts the negative impact on wages in equilibrium. However, my model has additional channels to amplify the general equilibrium effects. First, change in income leads to demand shift of workers due to non-homothetic preference, therefore feedback loop in goods market: lower income leads to less demand for the services sector. Second, there is friction in the workers' adjustment due to the exposure effect in the local labor market. These effects play out across space. Therefore, the overall impacts on individuals are different across locations, leading to the different consequences in their mobility.

I undertake counterfactuals for the fundamental productivity and amenities, respectively. In the first subsection, I consider the impact of productivity shocks on structural change, welfare and intergenerational income mobility of workers. This allows me to study the importance of technological progress in shaping individual-level consequences in the last decades. In the second subsection, I undertake the counterfactuals when there are shocks in the fundamental amenities. Specifically, I consider the lower barrier for migration across CBSAs. The counterfactual experiment reveals the importance of the location specific environment to explain the spatial pattern of structural change and labor mobility. In addition, for both productivity and amenities, I undertake the counterfactuals where the productivity and amenities become uniform across space. The motivation for this counterfactual is twofold. First, I aim to understand the persistent role of *ex-ante* differences in fundamentals to explain the equilibrium allocation in the later period. Second, it is useful to think about the future of the economy where the spatial productivity differences or spatial misallocation tend to decline with development. In the counterfactual experiments, the economy starts from the actual equilibrium observed in the data in 1980. Then, I implement the changes in the fundamentals to solve the counterfactual equilibrium. The uniqueness of the dynamic equilibrium is not guaranteed in the presence of spillovers in productivity and inter-sectoral linkages in production. Therefore, I compute the counterfactual equilibrium with the observed equilibrium as a starting point. I also run the model with a small perturbation of the initial equilibrium to assess the local uniqueness of the counterfactual equilibrium.

VII.A Productivity Changes

Productivity Shocks. The first set of counterfactuals assume that there are negative shocks on the fundamental productivity. I undertake the first counterfactual where fundamental productivity of services sector ($\{A^j_{i,t}\}_{j\in Service}$) is dropped by 10 percent in 1990 relative to the observed level and fixed at the level for the later periods, 2000 and 2010. Therefore, the fundamental productivity of all service industries is fixed at the 90 percent of the level of 1990 throughout time. In the second counterfactual, I focus on particular industries. Over the last decades, the main driver of TFP growth has been the industries relating to information technology (IT). As discussed in the previous section, the IT intensive industry such as FIRE has shown a significant increase of TFP in CBSAs in the U.S. economy. To see the role of such a rise in IT intensive industries in the service sector, I assume that there were no such positive technological progress in IT intensive service industries, including FIRE and communication service. I set their productivity at 90 percent of the level in 1990 throughout time. Further, I also consider the technological progress in the manufacturing sector for the comparison of their impacts. In particular, I focus on industries that use robots intensively, the electric and computer industry and transport equipment.[27] I set lower productivity for these two industries in the same manner as services.

In the Panel A of Table 2, I report the results for these three counterfactuals about the TFP changes and structural changes. The rows for the first counterfactual experiment (i) shows the negative impact on services sector TFP ($\delta^{Service}_{i,t}$) defined in (31). In 1990, it shows 8.5 percent lower than the baseline economy. 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 productivity shocks in the initial period can be faded out through workers' mobility over generations. I also find an increase in the variation of the negative effect over time. This implies large heterogeneity in adopting the negative shocks across CBSAs. Row 2 in Panel A shows the difference in the employment share of services to the baseline economy. When turning off the technological progress in the service sectors, I see a large drop in the employment share of services. This happens for two reasons, as I discussed above. The first channel is the traditional effect of factor mobility across sectors. The second channel is an additional impact of the demand driven structural changes. When I 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 slow down. Therefore, it further prevents the labor shift to services. This mechanism through the demand side is fundamental as I see its effect in the counterfactual (iii) in the table. In the counterfactual (iii), I do not introduce the direct negative shocks to the services sector, but I see a low employment share compared to the baseline. For the counterfactual (ii), I see the average negative effect on sector level TFP in 1990 and 2000, while it turns out to be positive in 2010. This is also consistent with the consequences of labor adjustment.

In Table 3, I report the results for the impact on welfare. For each counterfactual, the first Row shows the average percentage change of the welfare dynamics ($\mathrm{d}\ln V_{i,t}$), and other rows show those for different margins in (32). The average of changes in welfare dynamics is small over periods, but there is a large varia-

[27] These industries show the highest penetration rate of robots in the U.S. economy (Acemoglu and Restrepo 2020).

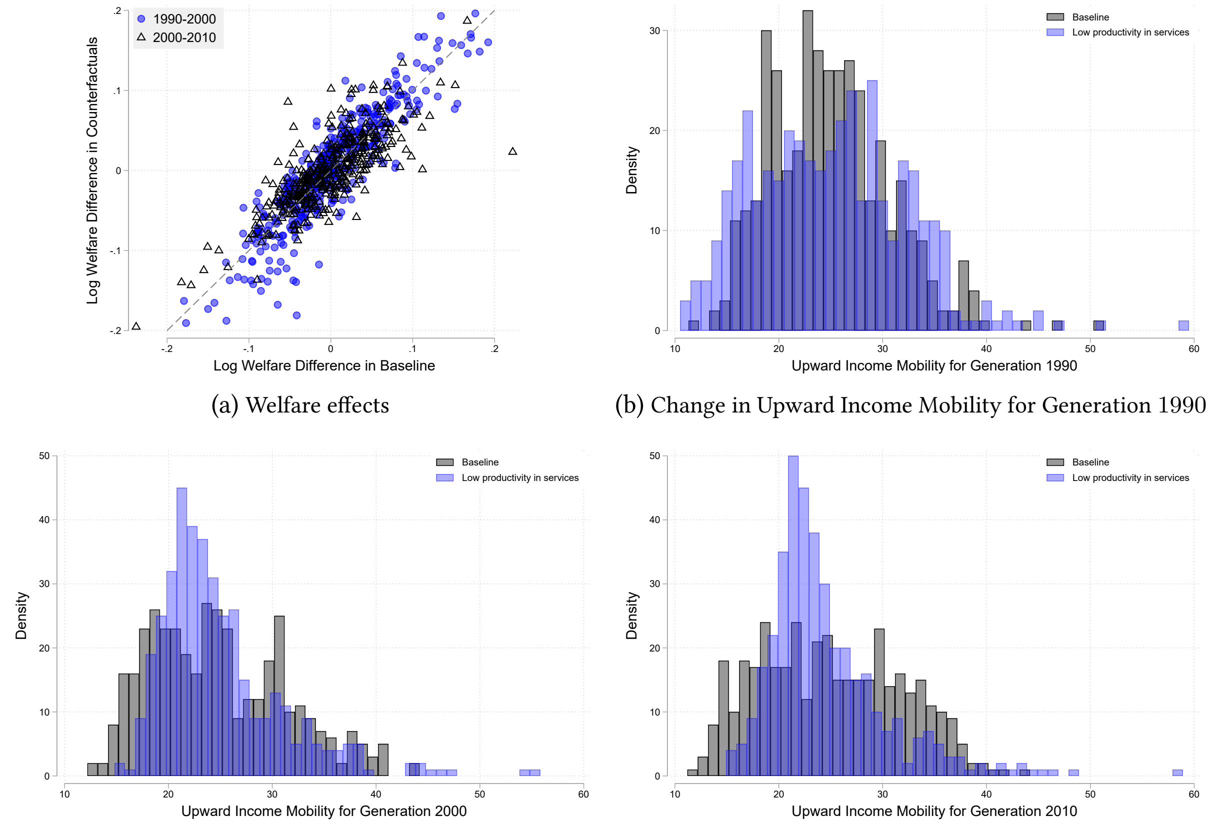
tion. The standard deviation of the changes shows 3.2 for generation 2000 and generation 1990, and 3.1 for generation 2010 and 2000. The pattern is the same for other counterfactuals (ii) and (iii). When I investigate the margins, the main contribution for the change of welfare dynamics is the gains from consumption and the gains also exhibit large variation. This confirms that the negative productivity shocks create a large variation in real income across CBSAs Part of this result is due to the fluctuation of housing prices. As I showed in Proposition 5, a large variation of real income is associated with a large variation of housing prices. Among other mechanisms, counterfactual migration gains show large values compared to the job opportunity gains. Yet, I find a substantial variation of these two margins across CBSAs. Their inter-quantile ranges are similar to those of changes in welfare dynamics.

Next table 4 reports the impact on intergenerational income mobility. Row 1 to 3 show the results for the first set of counterfactuals. For each generation, I report the percentile change of $\widetilde{M}_{i,t}$ in (33) from the baseline economy. 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 smaller effects. However, the generations of 2000 and 2010 show higher upward mobility on average. For generation 2000, individuals experience around 5 to 6 percentage increase in the upward mobility compared to the baseline economy. The logic for this result is the following. When the exogenous productivity is absent, the endogenous spillover in productivity becomes salient, and workers sort into the place with agglomeration. In addition, as I see in welfare results, a larger variation of real income growth creates workers' mobility both across locations and sectors. Together with these endogenous responses of workers, I see higher upward mobility on average, but with large variation in its gain. The variation in the change of intergenerational income mobility becomes large over time.

Figure 19 present the welfare effects and change in intergenerational income mobility across 395 CBSAs when undertaking the counterfactual for the low productivity in all service industries. In Panel (a), I find the variation of welfare effects across CBSAs. For the welfare difference between generation 1990 and 2000, $\mathrm{d}\ln V_{i,2000}$, the CBSAs with welfare losses show further welfare losses in the counterfactual. The technological progress in services and structural transformation benefit these CBSAs in the baseline economy. 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 negative impact on the productivity of services leads to a large variation of upward income mobility for the generation 1990. Once the productivity of services is fixed after 1990, Panels (c) and (d) show less variation of upward mobility.

Spatial Variation of Fundamental Productivity I next consider another counterfactual for fundamental productivity: eliminating the variation of fundamental productivity differences on geography. I set the fundamental productivity of industry j in period t such that $\widetilde{A}_t^j = \left(\prod_i A_{i,t}^j\right)^{1/N}$. The average productivity grows over time, but the evolution is same across CBSAs. In Panel A of Table 2, I report the results for this counterfactual in (iv). Compared to the baseline economy, I find that the service sector TFP shows 7.6 percent higher in 1990 and reaches 15.1 percent in 2010 on average, and most CBSAs exhibit TFP growth in the service sector. This is consistent with the implication of the agglomeration economies. Once I abstract the exogenous variation, industrial locations are subject to strong agglomeration forces due to the spillover in productivity. Since the strength of local agglomeration economies is strong for service sectors (γ_j), I can see an increase of service sectors TFP and an increase of the standard deviation. The decline of employment share is small relative to counterfactuals (i) to (iii). This implies that the benefit of agglomerations counteracts the slow structural change. The endogenous spillover works for the welfare changes in Table 3. When I compare the numbers to counterfactuals (i) to (iii), both average welfare change and change in standard deviation show significant increases. In Row (iv) of Table 4, I see the positive effects on the upward mobility of workers. These findings conclude that the spatial variation of productivity mitigates the polarization of locations in terms of welfare dynamics and upward income mobility. Without such exogenous productivity differences, individual consequences in terms of intergenerational income mobility are crucially shaped by the place they have an origin, while they may benefit on average.

Figure 19: Welfare Effects and Intergenerational Income Mobility for the Productivity Change in Services



(a) Welfare effects (b) Change in Upward Income Mobility for Generation 1990

(c) Change in Upward Income Mobility for Generation 2000 (d) Change in 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 service industries (transport service, wholesale trade, retail, FIRE, health service, education and legal, communication service and other services) 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, $\mathrm{d}\ln V_{i,t}$. Blue dots (black triangles) show the welfare differences between generations 1990 and 2000 (2000 and 2010), respectively. In panels (b), (c) and (d), I report the distribution of upward income mobility for different three generations, generation 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.

VII.B Amenities and Migration Barriers

The second set of experiments undertakes the counterfactuals for the fundamental location characteristics in amenities. As I discussed in the previous sections, I used the model structure to obtain the overall amenities for workers in any particular CBSA and industry. By construction, the variation of overall amenities across space include both the variation of fundamental benefit ($B^s_{i,t}$) and migration barrier ($M_{i,t}$). Then, I start with the lower migration barrier by 10 percent uniformly for every location. This benefits any workers in the economy, as it is isomorphic to an increase of benefit from residing and working in any particular location. Yet, workers' choices are not necessarily the same as the baseline since workers are ex-ante different in their origin, and the bilateral cost of migration defines the aggregate benefit of labor market access differently across workers. As another counterfactual about the migration barrier, I consider the case in which I set a 10 percent lower migration barrier for top CBSAs. I define the top 50 CBSAs based on the total employment size in 1980, selecting them for the counterfactual experiments. 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.

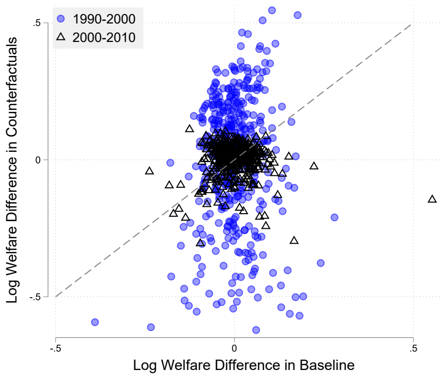
Panel B in Table 2 shows the results. In (v), I can find TFP growth in the services sector. On average, service sectors TFP exhibits 1.2 percent higher from the baseline economy in 1990 and it increases to 4.5 percent in 2010. In contrast, the employment share of the services sector is dropped compared to the baseline economy and the change shows large variation. This is rationalized by the specialization of workers in CBSAs that exhibit relatively high amenity and productivity. Once the migration barrier is lower, workers are directed to such CBSAs and the clustering of workers counteract the movement of workers across sectors due to the persistence in the model. More interestingly, when I compare the results between counterfactuals (v) and (vi), I find that lowering migration barrier for top 50 CBSAs has a similar impact of lowering migration barrier for all CBSAs. This suggests that workers directed sorting to the large cities are essential to consider the role of migration barrier in shaping the extent of structural change and TFP dynamics.

Turning to welfare, Panel B in Table 3 shows similar results as in the previous counterfactuals. The main driver of welfare dynamics is the change in the gains from consumption and their effects are persistent over generations. In Table 4, I find that upward mobility becomes high when I have a low migration barrier. This is consistent with the theory and quantitative analysis in the previous sections. Individuals are able to sort into the location with a higher return for any particular industry, and they have more opportunities to climb up the income ladder by the location choices. I also confirm that this mechanism is mainly at work for the migration to the large cities by comparing the similar magnitude in two counterfactuals (v) and (vi).

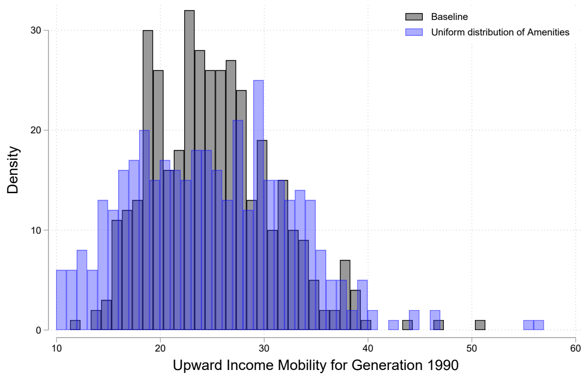
Spatial variation of amenities. Lastly, I investigate the role of differences in fundamental amenities across CBSAs. To this end, I perform the counterfactual in which overall amenities develop at the same rate across all CBSAs given any particular industry s. This implies that workers in any particular industry face the same level of amenities across CBSAs in each period. As reported in (vii) in Table 2, this further benefits the TFP growth of the services sector. Once I turn off the difference of fundamental amenities among CBSAs, I predict a 7.1 percent increase in service sector TFP on average in 1990, and it becomes 14.16 percent in 2010. Compared to the results in the counterfactual (iv), I see a similar magnitude for the average changes but less variation. This is intuitive since equalizing productivity has both a direct effect and indirect effect of fostering the TFP growth, while equalizing the amenities has only indirect effects through mobility. In Table 3, I find the largest welfare gains among the counterfactuals. In (vii), welfare dynamics is larger than baseline economy by 2.8 percent for the generations 1990 and 2000, and it is 0.3 percent for generations 2000 and 2010. When I see the decomposition of the effect, this substantial effect in welfare dynamics arises through the gains from a job opportunity. When the value of amenities is the same across CBSAs, workers' industry choice and location choice are purely determined by the return of industry choice in the current location. Therefore, individuals achieve large gains from job opportunities. In Table 4, I also find substantial positive effects on intergenerational income mobility. This is also consistent with the benefit from job opportunities in the local labor market. When eliminating the variation of amenities across locations, individuals are more likely to achieve a higher position of income rank compared to the previous generation. 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.

Figure 20 present the welfare effects and change in intergenerational income mobility across 395 CBSAs for the last counterfactual experiment where I set uniform values of amenities across CBSAs for any particular industry. In Panel (a), the spatial variation in welfare differences between generation 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 of 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. In Panel (b), (c) and (d), I show the distribution of upward income mobility across CBSAs in the counterfactual. As in the welfare effects, the upward income mobility for generation 1990 exhibits a larger variation in the counterfactual than the baseline, while the negative impact is 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 persistency after the change in the early period.

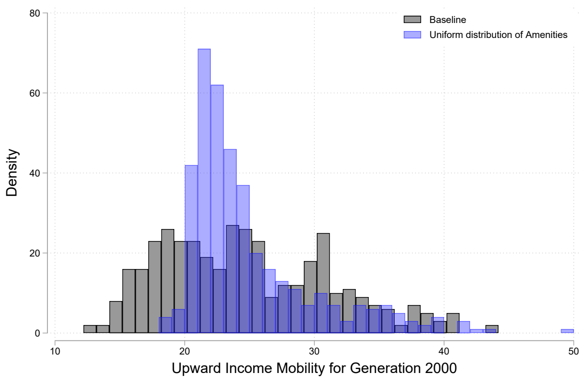
Figure 20: Welfare Effects and Intergenerational Income Mobility for the Uniform Distribution of Amenities



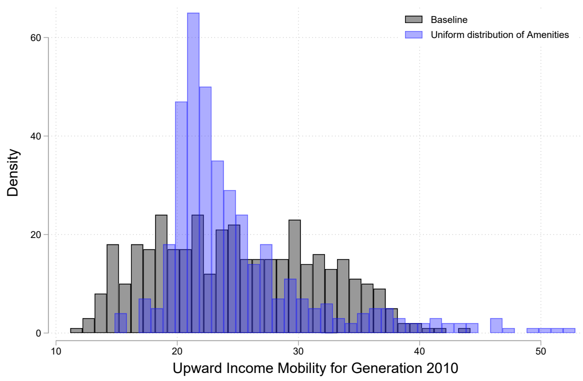
(a) Welfare effects



(b) Change in Upward Income Mobility for Generation 1990



(c) Change in Upward Income Mobility for Generation 2000



(d) Change in 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, $\mathrm{d}\ln V_{i,t}$. Blue dots (black triangles) show the welfare differences between generations 1990 and 2000 (2000 and 2010), respectively. In panels (b), (c) and (d), I report the distribution of upward income mobility for different three generations, generation 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.

Table 2: Counterfactual Experiments – Impact on Service TFP and Change in Service Employment Share

Panel A			1990				2000				2010			
			Mean	SD	25prc	75prc	Mean	SD	25prc	75prc	Mean	SD	25prc	75prc
(i)	Low Productivity	Service TFP	−8.522	2.320	−10.035	−6.883	−7.515	4.255	−9.095	−5.485	−6.074	5.482	−8.809	−3.542
	in All Services	Service Emp. Share	−13.107	5.038	−16.470	−9.453	−17.467	5.473	−21.454	−13.602	−21.582	5.863	−26.231	−17.288
(ii)	Low Productivity in	Service TFP	−2.139	2.392	−3.629	−0.623	−1.141	2.681	−2.739	0.288	0.433	4.132	−1.587	2.448
	IT intensive services	Service Emp. Share	−13.843	5.115	−17.294	−10.126	−19.027	5.644	−23.355	−14.709	−23.272	6.075	−27.965	−18.357
(iii)	Low Productivity in	Service TFP	1.187	2.5834	−0.508	3.004	1.622	2.42	−0.034	3.3224	4.295	5.299	1.669	6.486
	Robot intensive manufacturing	Service Emp. Share	−14.347	5.143	−17.926	−10.598	−20.277	5.824	−24.6534	−16.077	−25.323	6.332	−30.241	−20.596
(iv)	Uniform Productivity	Service TFP	7.639	7.473	3.041	11.855	7.891	7.702	3.559	12.236	15.167	11.354	7.888	22.172
	Change across Space	Service Emp. Share	−10.195	5.274	−13.712	−6.698	−13.972	6.295	−18.615	−9.7854	−18.194	6.687	−22.77	−13.72
Panel B			1990				2000				2010			
			Mean	SD	25prc	75prc	Mean	SD	25prc	75prc	Mean	SD	25prc	75prc
(v)	Low Migration Barrier	Service TFP	1.254	2.581	−0.439	3.065	1.761	2.42	0.104	3.47	4.506	5.339	1.85	6.632
	for All CBSAs	Service Emp. Share	−14.165	5.128	−17.667	−10.403	−19.812	5.704	−24.236	−15.567	−24.54	6.09	−29.26	−20.091
(vi)	Low Migration Barrier	Service TFP	1.295	2.599	−0.417	3.044	1.827	2.455	0.16	3.469	4.588	5.369	1.904	6.758
	for Top 50 CBSAs	Service Emp. Share	−14.169	5.135	−17.656	−10.432	−19.823	5.712	−24.161	−15.492	−24.548	6.1	−29.166	−20.129
(vii)	Uniform Amenities	Service TFP	7.151	3.781	4.901	9.248	9.867	5.209	7.555	12.979	14.167	6.222	11.017	17.183
	Change across Space	Service Emp. Share	−10.867	8.401	−16.432	−5.82	−15.193	9.357	−21.35	−9.145	−15.017	10.303	−20.892	−9.246

Note: For each counterfactual scenario (i) to (vii), I report the percentage change of aggregate TFP in the services sector and the change of employment shares in the service sector from the baseline economy. For each year, 1990, 2000 and 2010, I show the mean, standard deviation, 25 percentile and 75 percentile values across 395 CBSAs in the U.S. economy. Units of all entries are percentages. Panel A report results of counterfactual exercises about productivity changes. Counterfactual (i) undertakes counterfactuals when fundamental productivity of all service industries (transport service, wholesale trade, retail. FIRE, health service, education and legal, communication service and other services) is dropped by 10 percent in 1990 and the fundamental productivity level is unchanged later. The counterfactual (ii) suppose that fundamental productivity of IT intensive services (FIRE and communication services) is lower than baseline by 10 percent in 1990 and fixed over time. In the counterfactual (iii), I do the analogous experiment for robot intensive industries (electric and computer industry and transport equipment). The counterfactual (iv) undertakes when productivity growth of all industries is uniform across CBSAs. I take the geometric mean of fundamental productivities across locations for each sector in each period, and I assume that all CBSAs experience the same rate of fundamental productivity growth. Panel B reports counterfactuals about amenities. Counterfactual (v) undertakes the counterfactual in which migration barriers of all CBSAs are set to be 10 percent lower than the baseline in every period. In counterfactual (vi), I set a lower migration barrier for 50 CBSAs defined based on population in 1980. The counterfactual (vii) assumes that overall amenities are uniform across locations. I compute the geometric mean of overall amenities across CBSAs for workers in each sector, and I implement the value for all locations in each period.

Table 3: Counterfactual Experiments – Impact on Welfare

Panel A				1990 − 2000				2000 − 2010			
				Mean	SD	25 prc	75 prc	Mean	SD	25 prc	75 prc
(i)	Low Productivity in All Services	Welfare		0.052	3.219	−1.687	2.112	0.05	3.17	−1.971	1.733
			Consumption	0.126	5.181	−3.033	2.231	0.125	4.962	−2.453	3.231
			Migration Gain	0.08	3.897	−1.433	2.433	0.085	4.18	−2.256	1.698
			Job Opportunity Gain	0.052	3.201	−1.933	2.129	0.037	2.715	−1.729	1.885
(ii)	Low Productivity in IT intensive services	Welfare		0.044	2.945	−1.637	1.888	0.051	3.173	−1.923	1.713
			Consumption	0.126	5.196	−3.23	2.383	0.126	4.98	−2.457	3.131
			Migration Gain	0.078	3.841	−1.275	2.404	0.086	4.217	−2.257	1.691
			Job Opportunity Gain	0.049	3.102	−1.816	2.129	0.036	2.666	−1.737	1.768
(iii)	Low Productivity in Robot Intensive manufacturing	Welfare		0.044	2.963	−1.643	1.963	0.054	3.284	−2.004	1.859
			Consumption	0.133	5.344	−3.457	2.461	0.142	5.282	−2.725	3.238
			Migration Gain	0.081	3.912	−1.51	2.326	0.1	4.554	−2.516	1.829
			Job Opportunity Gain	0.05	3.145	−1.772	2.046	0.039	2.766	−1.725	1.92
(iv)	Uniform Productivity Change across Space	Welfare		0.09	4.232	−2.277	2.507	0.067	3.664	−2.179	2.234
			Consumption	0.228	6.858	−3.65	3.735	0.229	6.772	−3.324	3.781
			Migration Gain	0.136	5.176	−2.165	2.94	0.164	5.796	−2.898	2.829
			Job Opportunity Gain	0.068	3.686	−1.818	2.349	0.06	3.454	−2.214	2.498
Panel B				1990 − 2000				2000 − 2010			
				Mean	SD	25 prc	75 prc	Mean	SD	25 prc	75 prc
(v)	Low Migration Barrier for All CBSAs	Welfare		0.043	2.924	−1.584	1.887	0.052	3.202	−1.882	1.879
			Consumption	0.121	5.112	−3.364	2.374	0.128	5.000	−2.548	3.142
			Migration Gain	0.074	3.737	−1.391	2.467	0.087	4.255	−2.265	1.705
			Job Opportunity Gain	0.049	3.124	−1.819	2.05	0.037	2.686	−1.648	1.893
(vi)	Low Migration Barrier for Top 50 CBSAs	Welfare		0.053	3.251	−1.917	1.895	0.053	3.247	−1.782	1.845
			Consumption	0.121	5.104	−3.399	2.68	0.128	5.004	−2.509	3.231
			Migration Gain	0.075	3.745	−1.519	2.419	0.087	4.26	−2.272	1.73
			Job Opportunity Gain	0.058	3.406	−1.945	2.165	0.038	2.727	−1.73	1.794
(vii)	Uniform Amenities Change across Space	Welfare		2.89	23.375	−13.812	21.407	0.344	7.944	−3.45	5.546
			Consumption	0.852	13.383	−9.98	9.665	0.116	4.737	−2.376	2.755
			Migration Gain	0.901	13.254	−7.365	9.403	0.675	11.274	−5.116	7.315
			Job Opportunity Gain	2.374	21.418	−14.399	18.771	0.244	6.851	−3.274	4.858

Note: For each counterfactual (i) to (vii), I report percentage change of the welfare differences over generations. Welfare differences are defined for between generation 2000 to 1990 and 2010 to 2000. I show the mean, standard deviation, 25 percentile and 75 percentile values of their changes across 395 CBSAs in the U.S. economy. Units of all entries are percentages. Panel A report results of counterfactual exercises about productivity changes. Panel B reports counterfactuals about amenities. See note of Table 2 for more details of counterfactuals.

Table 4: Counterfactual Experiments – Impact on Intergenerational Income Mobility

Panel A		1990				2000				2010			
		Mean	SD	25 prc	75 prc	Mean	SD	25 prc	75 prc	Mean	SD	25 prc	75 prc
(i)	Low Productivity in All Services	−0.772	13.405	−7.408	8.752	5.612	30.591	−16.232	23.18	6.692	36.848	−19.431	27.432
(ii)	Low Productivity in IT intensive services	−0.799	13.596	−7.552	9.003	5.396	30.236	−17.408	23.461	5.971	35.18	−17.739	23.469
(iii)	Low Productivity in Robot intensive manufacturing	−0.82	13.792	−7.72	9.128	5.332	29.536	−16.303	23.62	5.802	35.517	−18.338	24.659
(iv)	Uniform Productivity Change across Space	−1.089	15.73	−9.982	10.029	6.399	44.263	−22.205	24.941	7.511	52.466	−26.36	29.747
Panel B		1990				2000				2010			
		Mean	SD	25 prc	75 prc	Mean	SD	25 prc	75 prc	Mean	SD	25 prc	75 prc
(v)	Low Migration Barrier for All CBSAs	−0.821	13.754	−7.792	9.182	5.342	29.915	−16.806	23.297	5.621	34.982	−18.316	23.462
(vi)	Low Migration Barrier for Top 50 CBSAs	−0.814	13.779	−7.6	9.264	5.322	29.886	−17.243	23.004	5.634	34.956	−18.656	23.911
(vii)	Uniform Amenities Change across Space	−1.202	14.948	−6.838	7.264	9.222	41.652	−24.22	34.772	10.829	51.562	−27.384	30.928

Note: For each counterfactual (i) to (vii), I report percentage change of the intergenerational income mobility from the baseline values. For each year, 1990, 2000 and 2010, I show the mean, standard deviation, 25 percentile and 75 percentile values across 395 CBSAs in the U.S. economy. Units of all entries are percentages. Panel A report results of counterfactual exercises about productivity changes. Panel B reports counterfactuals about amenities. See note of 2 for more details of counterfactuals.

VIII 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, I 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. I have calibrated the model with the U.S. economy and despite the high number of dimensions – on location, industry and time – the model structure allows me to back out productivity and amenities from the data. And this, in turn, enables me 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 me 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.

My 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. These are issues at the top of the policy agenda not just in the U.S. but in countries across the world. In effect, my 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, I perform counterfactual experiments using the parameterized model, which enables me 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, I find that the productivity growth of industries that drive structural change and higher migration barriers limit upward mobility. In addition, the persistent variation in productivity and amenities across geographies is critical to explaining the regional disparity in TFP changes and workers' mobility. These results suggest they are critical to understanding how mobility can be encouraged and inequality in an economy that is increasingly dominated by services.

As seen in Figure 1, structural transformation shows uneven patterns across space in the U.S. While there has been sustained deindustrialization over the last half-century, manufacturing employment share remains high in most cities in the Rust Belt, including Buffalo, Cleveland, Detroit, Pittsburgh, and St. Louis. As late as the 1990s, the majority of Silicon Valley technology jobs were still in hardware, and the region was surrounded by fabrication plants building silicon semiconductors. Today, Silicon Valley has a very limited number of fabrication plants; however, it remains the dynamic global center of the communication service industries. Using the U.S. data, I show that the geographical variation of amenities and productivity spillovers are the main driver of such unevenness, and historical exposure to different industries creates persistence in the occupational structure. My paper demonstrates how different patterns of structural change across both space and time determine the geographical variation of welfare and the upward mobility of workers. 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.

The framework I 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. In recent work with Italo Colantone and Gianmarco Ottaviano (Colantone et al. 2021), I am looking at whether higher trade exposure to Chinese imports in the U.S. reduces social mobility, both in absolute and relative terms, conditioning for the initial level of inequality. The foundation of that paper is the framework I developed in this paper, which allows us to quantify the redistributive impacts of the trade shock across space and time. My model can also serve as a stepping-stone for analysis of the effects of other dynamic processes. Using my model, I plan to look at how environmental damages including climate change and air and water pollution might affect inequality and mobility across locations in the U.S. Another research avenue I plan to pursue is to apply 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 I have 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.

References

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy 128*(6), 2188–2244.

Allen, T. and C. Arkolakis (2014). Trade and the topography of the spatial economy. *The Quarterly Journal of Economics 129*(3), 1085–1140.

Allen, T. and C. Arkolakis (2018). Modern spatial economics: a primer. In *World Trade Evolution*, pp. 435–472. Routledge.

Allen, T. and D. Donaldson (2019). The geography of path dependence. *Unpublished manuscript*.

Anderson, J. E., C. A. Milot, and Y. V. Yotov (2014). How much does geography deflect services trade? canadian answers. *International Economic Review 55*(3), 791–818.

Arkolakis, C., A. Costinot, and A. Rodriguez-Clare (2012). New trade models, same old gains? *American Economic Review 102*(1), 94–130.

Artuç, E., S. Chaudhuri, and J. McLaren (2010). Trade shocks and labor adjustment: A structural empirical approach. *American economic review 100*(3), 1008–45.

Bairoch, P. (1991). *Cities and economic development: from the dawn of history to the present.* University of Chicago Press.

Baldwin, R. E. (2001). Core-periphery model with forward-looking expectations. *Regional science and urban economics 31*(1), 21–49.

Banerjee, A. V. and E. Duflo (2005). Growth theory through the lens of development economics. *Handbook of economic growth 1*, 473–552.

Barro, R. J., X. Sala-i Martin, O. J. Blanchard, and R. E. Hall (1991). Convergence across states and regions. *Brookings papers on economic activity*, 107–182.

Barro, R. T. and X. Sala-I-Martin (1992). Regional growth and migration: A japan-united states comparison. *Journal of the Japanese and International Economies 6*(4), 312–346.

Bartelme, D. G., A. Costinot, D. Donaldson, and A. Rodriguez-Clare (2021). The textbook case for industrial policy: Theory meets data. Technical report, National Bureau of Economic Research.

Behrens, K., G. Duranton, and F. Robert-Nicoud (2014). Productive cities: Sorting, selection, and agglomeration. *Journal of Political Economy 122*(3), 507–553.

Boar, C. and D. Lashkari (2021). Occupational choice and the intergenerational mobility of welfare.

Brezis, E. S. and P. R. Krugman (1997). Technology and the life cycle of cities. *Journal of Economic Growth 2*(4), 369–383.

Bryan, G. and M. Morten (2019). The aggregate productivity effects of internal migration: Evidence from indonesia. *Journal of Political Economy 127*(5), 2229–2268.

Buera, F. J. and J. P. Kaboski (2012). The rise of the service economy. *American Economic Review 102*(6), 2540–69.

Burstein, A., G. Hanson, L. Tian, and J. Vogel (2020). Tradability and the labor-market impact of immigration: Theory and evidence from the united states. *Econometrica 88*(3), 1071–1112.

Bütikofer, A., A. Dalla-Zuanna, and K. G. Salvanes (2019). Breaking the links: Natural resource booms and intergenerational mobility.

Caliendo, L., M. Dvorkin, and F. Parro (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. *Econometrica 87*(3), 741–835.

Caliendo, L. and F. Parro (2021). Trade policy. Technical report, National Bureau of Economic Research.

Caliendo, L., F. Parro, E. Rossi-Hansberg, and P.-D. Sarte (2018). The impact of regional and sectoral productivity changes on the us economy. *The Review of economic studies 85*(4), 2042–2096.

Caron, J., T. Fally, and J. R. Markusen (2014). International trade puzzles: A solution linking production and preferences. *The Quarterly Journal of Economics 129*(3), 1501–1552.

Caselli, F. and W. J. Coleman II (2001). The us structural transformation and regional convergence: A reinterpretation. *Journal of political Economy 109*(3), 584–616.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics 129*(4), 1553–1623.

Colantone, I., G. I. Ottaviano, and K. Takeda (2021). Trade and intergenerational income mobility: Theory and evidence from the us.

Combes, P.-P., G. Duranton, L. Gobillon, D. Puga, and S. Roux (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica 80*(6), 2543–2594.

Comin, D., D. Lashkari, and M. Mestieri (2020). Structural change with long-run income and price effects. *Econometrica.*

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives 27*(3), 79–102.

Corak, M. and P. Piraino (2011). The intergenerational transmission of employers. *Journal of Labor Economics 29*(1), 37–68.

Davis, M. A. and J. Heathcote (2005). Housing and the business cycle. *International Economic Review 46*(3), 751–784.

Desmet, K., D. K. Nagy, and E. Rossi-Hansberg (2018). The geography of development. *Journal of Political Economy 126*(3), 903–983.

Desmet, K. and E. Rossi-Hansberg (2009). Spatial growth and industry age. *Journal of Economic Theory 144*(6), 2477–2502.

Desmet, K. and E. Rossi-Hansberg (2014). Spatial development. *American Economic Review 104*(4), 1211–43.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980-2000. *American Economic Review 106*(3), 479–524.

Dix-Carneiro, R. (2014). Trade liberalization and labor market dynamics. *Econometrica 82*(3), 825–885.

Dix-Carneiro, R. and B. K. Kovak (2017). Trade liberalization and regional dynamics. *American Economic Review 107*(10), 2908–46.

Doepke, M. and F. Zilibotti (2008). Occupational choice and the spirit of capitalism. *The Quarterly Journal of Economics 123*(2), 747–793.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2012). The intergenerational transmission of risk and trust attitudes. *The Review of Economic Studies 79*(2), 645–677.

Dominitz, J. and C. F. Manski (1996). Eliciting student expectations of the returns to schooling. *Journal of Human resources*, 1–26.

Duranton, G. and D. Puga (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review 91*(5), 1454–1477.

Duranton, G. and M. A. Turner (2012). Urban growth and transportation. *Review of Economic Studies 79*(4), 1407–1440.

Eaton, J. and S. Kortum (2002). Technology, geography, and trade. *Econometrica 70*(5), 1741–1779.

Eckert, F. and M. Peters (2018). Spatial structural change. *Unpublished Manuscript*.

Fajgelbaum, P. D., E. Morales, J. C. Suárez Serrato, and O. Zidar (2019). State taxes and spatial misallocation. *The Review of Economic Studies 86*(1), 333–376.

Fan, T., M. Peters, and F. Zilibotti (2021). Service-led or service-biased growth? equilibrium development accounting across indian districts. Technical report, National Bureau of Economic Research.

Feigenbaum, J. J. (2015). Intergenerational mobility during the great depression.

Fernandez, R. and A. Fogli (2009). Culture: An empirical investigation of beliefs, work, and fertility. *American economic journal: Macroeconomics 1*(1), 146–77.

Fernández, R., A. Fogli, and C. Olivetti (2004). Mothers and sons: Preference formation and female labor force dynamics. *The Quarterly Journal of Economics 119*(4), 1249–1299.

Ferrie, J. P. (2005). History lessons: The end of american exceptionalism? mobility in the united states since 1850. *Journal of Economic Perspectives 19*(3), 199–215.

Fieler, A. C. (2011). Nonhomotheticity and bilateral trade: Evidence and a quantitative explanation. *Econometrica 79*(4), 1069–1101.

Fogli, A. and V. Guerrieri (2019). The end of the american dream? inequality and segregation in us cities. Technical report, National Bureau of Economic Research.

Gervais, A. and J. B. Jensen (2019). The tradability of services: Geographic concentration and trade costs. *Journal of International Economics 118*, 331–350.

Giannone, E. (2017). Skilled-biased technical change and regional convergence.

Glaeser, E. L., J. D. Gottlieb, and O. Ziv (2016). Unhappy cities. *Journal of labor economics 34*(S2), S129–S182.

Glaeser, E. L., S. P. Kerr, and W. R. Kerr (2015). Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics 97*(2), 498–520.

Glaeser, E. L., M. Resseger, and K. Tobio (2009). Inequality in cities. *Journal of Regional Science 49*(4), 617–646.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica*, 501–522.

Handbury, J. (2019). Are poor cities cheap for everyone? non-homotheticity and the cost of living across us cities. Technical report, National Bureau of Economic Research.

Hanoch, G. (1975). Production and demand models with direct or indirect implicit additivity. *Econometrica: Journal of the Econometric Society*, 395–419.

Head, K. and T. Mayer (2014). Gravity equations: Workhorse, toolkit, and cookbook. In *Handbook of international economics*, Volume 4, pp. 131–195. Elsevier.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2014). Growth and structural transformation. In *Handbook of economic growth*, Volume 2, pp. 855–941. Elsevier.

Hornbeck, R. and E. Moretti (2020). Who benefits from productivity growth? direct and indirect effects of local tfp growth on wages, rents, and inequality.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2019). The allocation of talent and us economic growth. *Econometrica 87*(5), 1439–1474.

Hsieh, C.-T. and E. Moretti (2019). Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics 11*(2), 1–39.

Huttunen, K., J. Møen, and K. G. Salvanes (2018). Job loss and regional mobility. *Journal of Labor Economics 36*(2), 479–509.

Keane, M. P. and K. I. Wolpin (1997). The career decisions of young men. *Journal of political Economy 105*(3), 473–522.

Kleinman, B., E. Liu, and S. J. Redding (2021). Suficient statistics for dynamic spatial economics.

Kramarz, F. and O. N. Skans (2014). When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies 81*(3), 1164–1200.

Krugman, P. (1991). History versus expectations. *The Quarterly Journal of Economics 106*(2), 651–667.

Lindquist, M. J., J. Sol, and M. Van Praag (2015). Why do entrepreneurial parents have entrepreneurial children? *Journal of Labor Economics 33*(2), 269–296.

Long, J. and J. Ferrie (2013). Intergenerational occupational mobility in great britain and the united states since 1850. *American Economic Review 103*(4), 1109–37.

Loury, L. D. (2006). Some contacts are more equal than others: Informal networks, job tenure, and wages. *Journal of Labor Economics 24*(2), 299–318.

Manski, C. F. (2000). Economic analysis of social interactions. *Journal of economic perspectives 14*(3), 115–136.

Matsuyama, K. (1991). Increasing returns, industrialization, and indeterminacy of equilibrium. *The Quarterly Journal of Economics 106*(2), 617–650.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of economic theory 58*(2), 317–334.

Matsuyama, K. (2009). Structural change in an interdependent world: A global view of manufacturing decline. *Journal of the European Economic Association 7*(2-3), 478–486.

Matsuyama, K. (2019). Engel's law in the global economy: Demand-induced patterns of structural change, innovation, and trade. *Econometrica 87*(2), 497–528.

McLaren, J. (2017). Globalization and labor market dynamics. *Annual Review of Economics 9*, 177–200.

Michaels, G., F. Rauch, and S. J. Redding (2012). Urbanization and structural transformation. *The Quarterly Journal of Economics 127*(2), 535–586.

Ngai, L. R. and C. A. Pissarides (2007). Structural change in a multisector model of growth. *American economic review 97*(1), 429–443.

Ossa, R. (2019). A quantitative analysis of subsidy competition in the us.

Ottaviano, G. I. (1999). Integration, geography and the burden of history. *Regional Science and Urban Economics 29*(2), 245–256.

Polanyi, M. (1958). Personal knowledge: Towards a post-critical philosophy. *University Of Chicago Press.*

Porcher, C. (2020). Migration with costly information.

Puga, D. and A. J. Venables (1996). The spread of industry: spatial agglomeration in economic development. *Journal of the Japanese and International Economies 10*(4), 440–464.

Rappaport, J. (2007). Moving to nice weather. *Regional Science and Urban Economics 37*(3), 375–398.

Redding, S. and A. J. Venables (2004). Economic geography and international inequality. *Journal of international Economics 62*(1), 53–82.

Redding, S. J. and E. Rossi-Hansberg (2017). Quantitative spatial economics. *Annual Review of Economics 9*, 21–58.

Redding, S. J. and D. M. Sturm (2008). The costs of remoteness: Evidence from german division and reunification. *American Economic Review 98*(5), 1766–97.

Rossi-Hansberg, E. and M. L. Wright (2007). Urban structure and growth. *The Review of Economic Studies 74*(2), 597–624.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics 125*(3), 1253–1296.

Simonovska, I. (2015). Income differences and prices of tradables: Insights from an online retailer. *The Review of Economic Studies 82*(4), 1612–1656.

Simonovska, I. and M. E. Waugh (2014). Trade models, trade elasticities, and the gains from trade. Technical report, National Bureau of Economic Research.