Centre for Economic Performance

Discussion Paper

ISSN 2042-2695

No. 2058
December 2024

Trade and intergenerational income mobility: Theory and evidence from the US

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Abstract
This paper studies the impact of globalization on intergenerational income mobility. Exploiting U.S. data, we find that stronger trade exposure at the commuting zone level lowers the intergenerational income mobility of residents. In particular, higher exposure to Chinese import competition lowers the income mobility of the cohort of U.S. workers born in 1980-1982. We present a general equilibrium theory in which path dependence in sector choice of individuals over generations and mobility frictions determine the dynamics of industrial compositions across locations in a country. The theory predicts that rising import competition reduces intergenerational income mobility, consistent with the empirical findings.

Key words: import competition, distributional consequences, intergenerational income mobility
JEL: F2; F14; F16

This paper was produced as part of the Centre's Trade Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We thank Guido Ardizzone, Giacomo Casali, Yuri Filippone, Sem Manna, and Chiara Soriolo for excellent re-search assistance. We are grateful to David Autor, Kerem Coşar, Rafael Dix-Carneiro, Gordon Hanson, and seminar participants at the 2023 ETSG Conference, the 2023 UEA meeting (Toronto), LSE and SMU for useful comments and suggestions. The usual disclaimer applies
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Published by
Centre for Economic Performance
London School of Economic and Political Science
Houghton Street, London WC2A 2AE

1 Introduction

Does globalization lower intergenerational income mobility? Several studies have documented a decline in social mobility in the United States, with significant variation across geographic areas (e.g., Ferrie 2005; Long and Ferrie 2013; Chetty et al. 2014; Chetty et al. 2017). At the same time, globalization has been shown to determine distributional consequences that raise inequality across workers and regions (e.g., Autor, Dorn, and Hanson 2013; Kovak 2013; Autor et al. 2014). In this paper, we connect these two phenomena and investigate the impact of trade exposure on intergenerational income mobility, both theoretically and empirically.

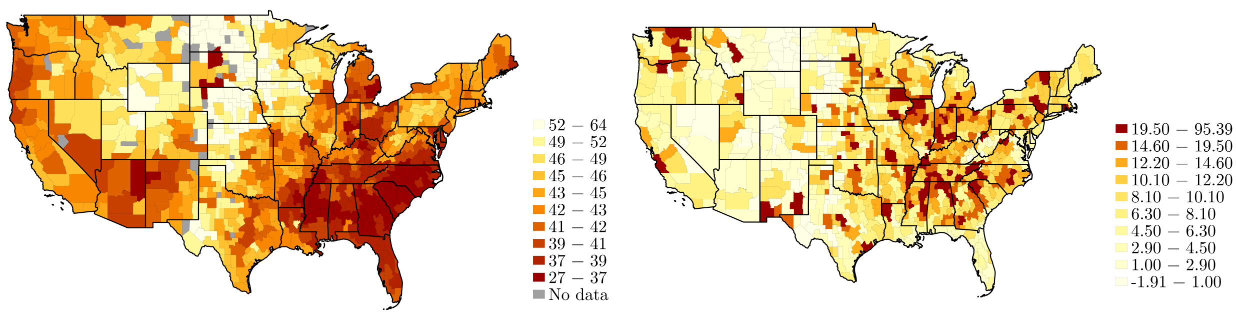
We begin by providing reduced-form evidence that individuals from regions characterized by higher exposure to import competition are constrained in their intergenerational income mobility. In particular, rising exposure to Chinese import competition between 1991 and 2007 lowers the mobility of the cohort of U.S. workers born in 1980-1982, as evaluated based on their income in 2011-2012, when they are in their early 30s. This evidence is robust to controlling for a large number of commuting zone characteristics, including the initial inequality in parents' income and a proxy for historical social mobility in the area, as well as to considering imports from different foreign countries.

To interpret these empirical results, we present a dynamic economic geography model with overlapping generations that features differential rates of structural transformation across locations, barriers for workers to switch locations due to migration costs, and barriers for workers to switch sectors due to their historical exposure to agglomeration in the birthplace. In theory, path dependence in sector choice of individuals over generations and mobility frictions determine the dynamics of industrial compositions across locations in a country. Exposure to import competition reduces intergenerational income mobility of workers through the interaction of lower wage growth and less opportunities to change job and location within a country. The numerical solutions of the theory show the reduction of intergenerational income mobility of workers from locations with relatively high exposure to a trade shock, consistent with our empirical findings for the U.S. Overall, our analysis points to globalization, by means of growing trade exposure, as a significant determinant of reduced intergenerational income mobility.

We start in Section 2 by describing our empirical strategy for evaluating the impact of trade exposure on intergenerational income mobility in the U.S. Throughout the paper, the primary data on income mobility are sourced from Chetty et al. (2014), and cover almost the universe of individuals born between 1980 and 1982. Their income is evaluated in 2011-2012, when they are aged around 30, and compared to their parents' income back in 1996-2000, at the time in which their important educational decisions were taken. As a main measure of income mobility we employ absolute upward mobility, defined as the average income rank of children born from parents in the bottom half of the national income distribution. The left-hand panel of Figure 1 shows a striking degree of heterogeneity in upward mobility across U.S. commuting zones. We exploit this variation for identification.

As for local trade exposure, we follow the approach by Autor, Dorn, and Hanson (2013) and combine the change in national imports from China with pre-sample data on employment composition in each commuting zone. In the main analysis we focus on import growth between 1991 and 2007, thus from the early stages of China's transformation until the peak of the so-called "China shock" before the financial crisis. The right-hand panel of Figure 1 shows the well-known heterogeneity in trade exposure across different areas of the U.S.

Figure 1: Intergenerational Income Mobility and Exposure to Chinese Imports



(a) Upward income mobility

(b) Exposure to import competition from China

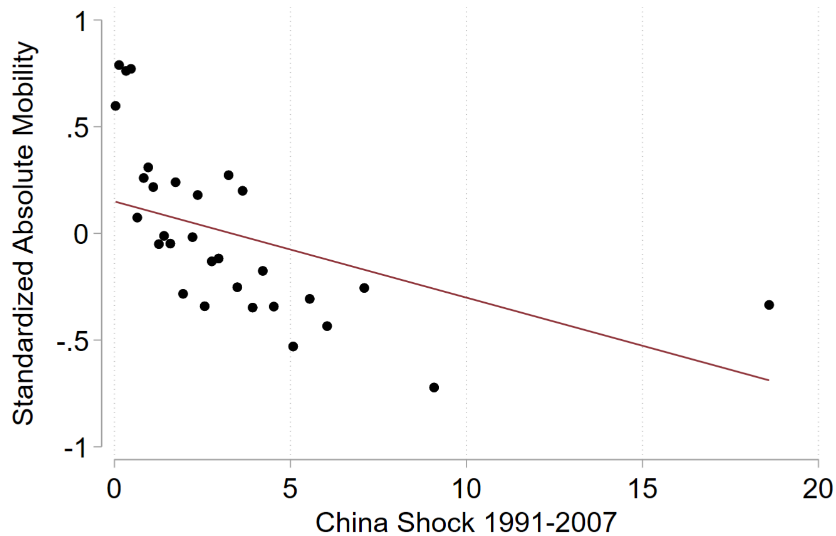
Note: Left map shows intergenerational income mobility, measured by absolute upward income mobility, across U.S. commuting zones. This measure is the average rank in the U.S. income distribution of children born from parents below the median of the U.S. income distribution (Chetty et al. 2014). Right map displays the exposure to import competition from China measured in thousands of U.S. Dollars (USD) per worker. See Section 2 for details.

Starting with the seminal contribution by Autor, Dorn, and Hanson (2013), a large literature has documented the effects of rising Chinese imports both in terms of worsening labor market outcomes and in terms of deteriorating health and social conditions in areas that were most exposed.[1] Building on this evidence, our analysis investigates the effect of trade exposure on intergenerational income mobility, which is affected by both economic and social determinants, and can thus be seen as a comprehensive, long-term indicator reflecting what Colantone, Ottaviano, and Stanig (2022) have called the "social footprint" of globalization.

As a stylized fact, Figure 2 shows evidence of a negative correlation between exposure to import competition from China and intergenerational income mobility at the level of commuting zones. In Section 3 we provide plausibly causal evidence on the negative effect of Chinese trade exposure on income mobility. As in Autor, Dorn, and Hanson (2013), imports from China to

[1] See Autor, Dorn, and Hanson (2016), Colantone, Ottaviano, and Stanig (2022), and Redding (2022) for reviews.

Figure 2: Intergenerational Income Mobility and Exposure to Chinese Imports



Note: This figure shows the bin scatter plot across U.S. commuting zones using 30 bins. Horizontal axis is the measure of exposure to import competition from China, and vertical axis is absolute upward mobility. See Section 2 for more information on the measures. The red line is the least-squares fit.

the U.S. are instrumented using Chinese exports to other countries. Our results are robust to measuring exposure to Chinese imports over different sub-periods and to considering different sources of imports (i.e., all trading partners, Mexico, and the full set of low-income countries). They are also robust to controlling for a wide array of initial characteristics of the commuting zones, encompassing economic, demographic, and social conditions.

Motivated by our empirical findings, in Section 4 we develop a dynamic economic geography model with overlapping generations that accommodates three key mechanisms: first, non-homothetic preferences between different sectors drive structural transformation; second, trade costs and productivity spillovers determine the endogenous pattern of the spatial distribution of different sectors; and third, individuals' choice of local labor markets drives labor allocation dynamics. In particular, individuals live for two periods, and during the first period, they choose the location and sector that will be the focus of the second period. Their location choice is determined by mobility costs and real income, whilst their sector choice reflects the future expected return and exposure to the previous generation's sectors of employment in their home local labor market. Intuitively, concentration of employment in any particular sector in a home location generates persistence in the sector choice of individuals over generations and this is microfounded by the information acquisition from the previous generation. Together with migration costs, this creates a path dependence in the local labor market over generations. We then characterize intergenerational income mobility by comparing the equilibrium income distribution of two generations. Trade shocks have heterogeneous effects on intergenerational income mobility across localities depending on the ex-ante employment composition and future pattern of labor allocation dynamics.

After describing the theoretical framework and its implications, in Section 5 we provide a numerical solution to the model. The parameterization of the model for two sectors and two countries with stylized geography in the home country allows us to show the trajectory of endogenous variables. Then, we show how the model can account for the empirical findings presented in Section 3. We first show that the numerical solutions qualitatively match the facts in the U.S. economy. In particular, the model is able to account for: (i) the declining labor share in the manufacturing sector; (ii) the relatively low upward income mobility for workers from locations with high manufacturing employment shares; and (iii) the negative correlation between upward income mobility and a measure of initial income inequality. Then, we examine the impact of a trade shock on the home country. To this end, we suppose that there is a positive shock to the productivity of the manufacturing sector in the foreign country. We find that home workers from locations with higher exposure to the trade shock experience a reduction in upward income mobility, and this is driven by the ex-ante concentration of the manufacturing sector and the persistence in sector choice of workers who stay in their home location. This implication of our theoretical framework is in line with empirical findings regarding the effect of trade exposure on the U.S. economy.

One potential channel through which trade exposure may decrease intergenerational income mobility is through reduced educational attainment. In line with that, in Section 6 we present three empirical results: (i) commuting zones with higher levels of college enrollment exhibit higher levels of upward income mobility; (ii) commuting zones with higher manufacturing employment shares display lower college enrollment pre-sample; and (iii) commuting zones characterized by higher trade exposure over the sample period witness a reduction in college enrollment.[2] We then extend the theory to account for educational choices. In theory, a trade shock can reduce educational attainment through two different mechanisms. First, the return on education is reduced as a result of the negative impact of the shock on local government revenues, which results in a decrease in public investment in education.[3] Second, the trade shock induces an incentive to switch location of work conditional on sector choice, thereby increasing the expected utility and compensating for a lower level of education. We lay out the extension of our base-

[2]This is consistent with the finding by Ferriere et al. (2021) that the negative impact of the China shock on labor market outcomes for adult workers in the U.S. is largely driven by the outcomes of those without college education. In addition, they show that college enrollment by young individuals from *low income* households decreased in U.S. regions more exposed to Chinese import competition.

[3]This channel is aligned with the finding by Feler and Senses (2017) that income shocks due to Chinese import competition in the U.S. result in a relative deterioration in the quality of local public goods.

line theory to include these mechanisms. The implications are consistent with the reduced-form evidence on the role of education.

This paper relates to different strands of existing research. First, we contribute to the reduced-form empirical literature on the effects of trade shocks on local labor markets, including Topalova (2010), Autor, Dorn, and Hanson (2013), Kovak (2013), Autor, Dorn, and Hanson (2016), Costa, Garred, and Pessoa (2016), Acemoglu et al. (2016), Pierce and Schott (2016), Dix-Carneiro and Kovak (2017), Batistich and Bond (2023). These studies investigate the distributional consequences of trade across individuals employed in different industries and living in different geographic areas. We focus on intergenerational income mobility, reaching beyond the direct effects of trade shocks on current workers. Our paper contributes to the literature by providing theory and evidence on how globalization can influence *both* inequality and mobility across different locations of a country. We highlight an additional, dynamic dimension of the distributional consequences of trade over generations that can play an important role in shaping people's assessment of globalization and their ensuing political behavior (see, e.g., Colantone and Stanig 2018a; Colantone and Stanig 2018b; Colantone, Ottaviano, and Stanig 2022).[4]

Our findings also contribute to the empirical studies that document how intergenerational income mobility of workers has been declining in the last decades in the U.S., including Ferrie (2005), Black and Devereux (2011), Long and Ferrie (2013), Chetty et al. (2014), Chetty et al. (2017), Hilger (2017), Tan (2023). While most of this literature provides evidence on the general pattern of declining intergenerational income mobility and its relation to local socioeconomic characteristics, a key focus of our paper is on the role of international trade in explaining the heterogeneous impact of structural transformation across regions and the resulting implications for income mobility.[5]

From a theoretical standpoint, our approach is related to recent trade literature that employs quantitative modeling to study the impact of trade shocks across local labor markets both in long-run (e.g., Kim and Vogel 2021; Redding 2022; Galle, Rodríguez-Clare, and Yi 2023) and in the transition dynamics (e.g., Artuç, Chaudhuri, and McLaren 2010; Dix-Carneiro 2014; Caliendo, Dvorkin, and Parro 2019; Traiberman 2019; Rodrıguez-Clare, Ulate, and Vasquez 2022). In this paper, we develop in a two-country setup a theoretical framework introduced by Takeda (2022). Our model builds on three important elements: (i) overlapping generations to characterize upward mobility; (ii) persistence in sectoral choices, with children choosing similar jobs as their

[4]Close to our work from an empirical point of view, Ahsan and Chatterjee (2017) find that trade liberalization in India has resulted in an increase in intergenerational *occupational* mobility for males in urban areas, due to a rise in the relative demand for skills. Recent evidence by Mitrunen (2024) points to positive effects of an export shock on intergenerational mobility in Finland, as driven by mandatory industrial exports to the Soviet Union after WWII.

[5]Outside of the U.S. context, recent studies provide evidence of geographic variation in intergenerational mobility within several countries (e.g., Corak 2020, Acciari, Polo, and Violante 2022, Bütikofer, Dalla-Zuanna, and Salvanes 2022, Bell, Blundell, and Machin 2023, Deutscher and Mazumder 2023).

parents; and (iii) moving costs across locations in the presence of idiosyncratic preference shocks, which are essential to explain the spatial heterogeneity of workers' adjustment to trade shocks.

The remainder of the paper is structured as follows. Section 2 presents data and variables on intergenerational income mobility and trade shocks, and describes our empirical strategy. Section 3 presents our main empirical results. Section 4 develops our theoretical model. Section 5 shows numerical solutions to the model and illustrates how it can qualitatively match the observations. Section 6 extends the analysis to focus on the education channel. Finally, Section 7 concludes.

2 Data, Measurement and Empirical Strategy

In this section we describe the data and variables used in the empirical analysis, and we present the empirical strategy.

2.1 *Intergenerational Income Mobility: Data and Measurement*

Data on intergenerational income mobility are sourced from Chetty et al. (2014). They are based on matched parents-children anonymized federal tax records from around 10 million American citizens born between 1980 and 1982, corresponding to around 90% of citizens in this birth cohort. For these individuals, Chetty et al. (2014) observe the following information: (i) parents' average total pre-tax household income between 1996 and 2000, when children are aged between 14 and 20, and thus major educational decisions are taken; (ii) parents' commuting zone of residence in 1996 (or earliest available year between 1996 and 2000); and (iii) children's average household income in 2011-2012, when they are aged around 30, which is when lifetime ranking in their cohort's national income distribution is essentially determined (Chetty et al. 2014).[6] Based on this information, two measures of intergenerational income mobility are computed at the level of commuting zones: absolute upward mobility and relative mobility.

The main measure of mobility we employ in the analysis is absolute upward mobility. This is defined as the average percentile rank in the national income distribution, relative to their own birth cohort, of children from families below the median of the national income distribution.[7] Introducing some notation, the degree of absolute upward mobility for the children's cohort of generation $t+1$, relative to their parents' generation t, in commuting zone i, is given by:

$$\text{Absolute Upward Mobility}_{it+1} = \mathbb{E}\left[\text{Rank}_{it+1}(\omega) \mid \text{Parent's Rank}_{it}(\omega) < 50\right] \tag{1}$$

It is important to notice that children contribute to the measurement of mobility in the commuting zone of origin even if they have moved somewhere else by the time their income is mea-

[6] We refer the reader to Chetty et al. (2014) for further information on the data.

[7] By construction, this is equivalent to the expected rank of children born from parents ranking at the 25th percentile of their respective national income distribution (Chetty et al. 2014).

sured. As a matter of fact, around 38 percent of children moved to a different commuting zone by 2012. Spatial mobility is itself a determinant of income mobility, which we always refer back to the relevant commuting zone at the time of educational investments and children's upbringing.

In an extension of the analysis, we employ relative mobility. This is defined as the correlation between children's income rank and their parents' income rank in the respective national income distributions (Dahl and DeLeire 2008; Chetty et al. 2014; Britto et al. 2022).[8] Results using relative mobility are consistent with those obtained using absolute upward mobility. We adopt the latter as the main measure of interest since increases in relative mobility (i.e., a lower rank-rank slope) could be undesirable if they are caused by worse outcomes for individuals born from richer families.

2.2 *Trade Exposure: Data and Measurement*

We compute exposure to Chinese imports at the commuting zone level following the methodology introduced by Autor, Dorn, and Hanson (2013). Specifically, we define:

$$\text{Import Exposure}_{it} = \sum_{j \in \mathcal{I}} \frac{L_{ijt}}{L_{it}} \cdot \frac{\Delta M_{\text{US}jt}}{L_{\text{US}jt}}, \tag{2}$$

where i indexes commuting zones, j manufacturing industries, and t years. $\Delta M_{\text{US}jt}$ is the change in real U.S. imports from China in industry j over the sample period beginning in year t. This is normalized by $L_{\text{US}jt}$, which is total U.S. employment in industry j at the beginning of the sample (1990). Industry weights L_{ijt}/L_{it} are the employment shares of industry j in commuting zone i at the beginning of the sample. Using initial employment figures, rather than figures that are updated over time, is meant to avoid endogeneity issues that may arise as a result of the import effects on employment.

Trade data are sourced from the UN Comtrade Database at the 6-digit product level, based on the 1992 Harmonized System (HS-92) classification. As in Autor and Dorn (2013), import figures are then aggregated at the 4-digit industry level based on the SIC classification, using the concordance by Pierce and Schott (2012). Employment data are sourced from the County Business Patterns (CBP).

According to equation (2), larger trade shocks are attributed to commuting zones where relatively more workers were initially employed in industries that later experienced larger increases in Chinese imports. In the main analysis, we focus on growth in Chinese imports between 1991 and 2007, thus from the early stages of China's transformation until the peak of the so-called

[8] This metric, also known as the rank-rank slope, measures the average dependence of children's incomes on those of their parents, thus capturing the "stickiness" of economic conditions across generations. Specifically, the rank-rank slope for a commuting zone is estimated as the coefficient from a linear regression of children's income rank on that of their parents. See Section A of the Online Appendix for more details.

"China shock" before the financial crisis. In an extension of the analysis, we then consider two different sub-periods, 1991–1995 and 2001–2007, obtaining consistent results.

We regress income mobility on trade exposure. A possible concern with this approach is related to the endogeneity of import competition. For instance, growth in Chinese imports could be endogenous to domestic demand and supply shocks in the U.S., that are in turn related to income mobility. We address this concern by adopting the same instrumental variables strategy as in Autor, Dorn, and Hanson (2013). Specifically, we instrument the change in imports from China in the U.S. using the change in Chinese imports in a set of eight other high-income countries.[9] The instrument is defined as:

$$\text{Import Exposure IV}_{it} = \sum_{j \in \mathcal{I}} \frac{L_{ijt-10}}{L_{it-10}} \cdot \frac{\Delta M_{\text{Other}jt}}{L_{\text{US}jt-10}}, \tag{3}$$

where $\Delta M_{\text{Other}jt}$ is the growth in Chinese imports in other countries, and all employment figures are lagged by 10 years compared to (2), to further reduce simultaneity bias. Intuitively, this IV approach is meant to capture the variation in import competition in the U.S. that is driven by exogenous changes to supply conditions in China, rather than by potentially endogenous domestic factors in the U.S. In fact, supply changes in China are likely to generate at the same time higher exports not only to the U.S. but also to other high-income countries.

While trade exposure to China is our main focus, we also show that our results are robust when considering alternative import sources, including total imports from all trading partners, imports from a set of low-income countries, and imports from Mexico.

2.3 *Empirical Specification*

Our aim in the reduced-form analysis is to estimate the effect of trade exposure on intergenerational income mobility. To this purpose, we estimate specifications of the following form:

$$\text{Mobility}_{i,\text{'80-'82}} = \alpha_{K(i)} + \beta \text{ Import Exposure}_{it} + \gamma \text{ Initial Inequality}_{it} + \varepsilon_i, \tag{4}$$

where $\text{Mobility}_{i,\text{'80-'82}}$ is a standardized measure of intergenerational income mobility for workers from the 1980-1982 birth cohort in commuting zone i. As outlined in Section 2.1, this is computed using information on their incomes in 2011-2012. In the main analysis we use absolute upward mobility, while relative mobility is used for robustness checks. $\text{Import Exposure}_{it}$ is the exposure to import competition in commuting zone i, as defined in equation (2). In the main analysis we focus on import competition from China between 1991 and 2007. Different sub-periods and sources of imports are considered in additional analyses.

[9] These are: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Initial Inequality$_{it}$ is a control for inequality in parents' incomes at the commuting zone level. This is important in light of the so-called "Great Gatsby Curve" empirical regularity (Krueger 2012). This refers to the fact that locations with higher income inequality in the current period tend to exhibit lower intergenerational income mobility in the future period. Following Chetty et al. (2014), we employ four different measures of income inequality at the commuting zone level: the Gini coefficient; the Gini coefficient computed on the bottom 99 percent of the income distribution; the share of total income earned by the top 1 percent; and the share of households in the interquartile of the income distribution, which is a proxy for the size of the middle class. $\alpha_{K(i)}$ are fixed effects denoting the U.S. Census region K to which commuting zone i belongs,[10] while ε_i is an error term.

3 Emprical Analysis

3.1 *Main Results*

Table 1 displays the baseline estimates of equation (4). Import exposure refers to the change in Chinese imports between 1991 and 2007. We estimate four different specifications, one without a control for initial inequality in parents' incomes, the others including different controls for it, as in Chetty et al. (2014). For each specification there are two columns: one shows the ordinary least squares (OLS) estimates, the other presents the instrumental variables (IV) results, where the import shock is instrumented using Chinese imports in other countries, as outlined in equation (3). All specifications include fixed effects for U.S. Census regions, and standard errors are always clustered at the state level.

The coefficient on import exposure is negative and statistically significant across the board. This points to a negative effect of exposure to Chinese imports on intergenerational income mobility. The IV estimates are always larger in absolute value than the OLS ones. This is consistent with there being unobserved factors, such as positive demand shocks, that are associated at the same time with higher imports and higher income mobility. The first-stage coefficient on the instrument is positive and significant and the F-statistic does not signal a weakness problem, in line with earlier results by Autor, Dorn, and Hanson (2013).

In terms of magnitudes, the IV estimate in Column (2) suggests that a 1,000 U.S. Dollar increase in Chinese imports per worker in a commuting zone, over 1991–2007, leads to a 0.098 standard deviation decrease in absolute upward mobility. Put differently, one standard deviation increase in exposure to Chinese imports leads to a 0.4 standard deviation decrease in absolute upward mobility. The estimated effect remains very stable across the other IV regressions in Columns (4), (6) and (8), and is far from negligible. For instance, to put it in perspective, Chetty et al. (2014)

[10] Those are the four U.S. Census Regions defined by the United States Census Bureau.

Table 1: Trade Exposure and Income Mobility in the U.S.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Absolute upward income mobility							
Exposure to Chinese imports '91-'07	-0.031^c	-0.098^a	-0.032^b	-0.103^a	-0.034^b	-0.109^a	-0.034^b	-0.093^a
	(0.015)	(0.031)	(0.015)	(0.029)	(0.015)	(0.027)	(0.014)	(0.030)
Gini coefficient			-0.483^a	-0.490^a				
			(0.070)	(0.071)				
Gini bottom 99%					-0.613^a	-0.628^a		
					(0.069)	(0.069)		
Top 1% income share					-0.137^a	-0.136^a		
					(0.030)	(0.032)		
% households in middle class (p25-75)							0.608^a	0.617^a
							(0.093)	(0.092)
Estimation	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	693	693	693	693	693	693	693	693
R-squared	0.27	-	0.41	-	0.48	-	0.49	-
First-Stage Results								
Exports to high income countries	-	0.938^a	-	0.938^a	-	0.938^a	-	0.940^a
	-	(0.154)	-	(0.154)	-	(0.155)	-	(0.152)
Kleibergen-Paap F-Statistic	-	37.33	-	37.26	-	36.65	-	38.17
Anderson-Rubin p-value	-	< 0.01	-	< 0.01	-	< 0.01	-	< 0.01

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Columns (1), (3), (5) and (7) report OLS estimates; Columns (2), (4), (6) and (8) report IV estimates. [a] and [b] indicate significance at the 1 and 5 percent levels, respectively.

find that a one standard deviation increase in the high-school dropout rate at the commuting zone level is associated with a decline in absolute upward mobility by 0.29 of a standard deviation, and a one standard deviation increase in racial segregation is associated with a 0.36 standard deviation decline in mobility.

Consistent with the "Great Gatsby Curve" empirical regularity, we detect a negative relation between initial inequality in parents' income and subsequent mobility in Columns (3) to (8). Specifically, higher levels of the Gini coefficients and a higher share of income for the top 1 percent are related to lower mobility, while the share of households in the interquartile of the national income distribution is positively associated with mobility. Given the similarity of results across specifications, we adopt the specification in Columns (3)–(4), which includes the standard Gini coefficient, as our baseline for all the extensions and robustness checks that are presented in what follows.

The surge in trade exposure between 1991 and 2007 could have an impact on income mobility for the 1980–1982 birth cohort in two ways. First, the shock could affect the income of parents and therefore the choices in terms of human capital investment made between 1996 and 2000. Second, it could affect employment opportunities by the time children finish their studies and enter the labor market, with the ensuing impact on their income measured in 2011-2012. In the

Table 2: Chinese Imports over Different Periods

	(1)	(2)	(3)	(4)
Dependent variable:	Absolute upward income mobility			
Exposure to Chinese imports '01-'07	-0.047^{b}	-0.137^{a}		
	(0.023)	(0.038)		
Exposure to Chinese imports '91-'95			-0.137^{b}	-0.669^{b}
			(0.052)	(0.292)
Gini coefficient	-0.484^{a}	-0.493^{a}	-0.480^{a}	-0.482^{a}
	(0.070)	(0.071)	(0.070)	(0.071)
Estimation	OLS	IV	OLS	IV
Area Fixed Effects	Yes	Yes	Yes	Yes
Observations	693	693	693	693
R-squared	0.41	-	0.40	-
First-Stage Results				
Exports to other high income countries	-	1.050^{a}	-	0.544^{a}
	-	(0.132)	-	(0.118)
Kleibergen-Paap F-Statistic	-	63.00	-	21.41
Anderson-Rubin p-value	-	< 0.01	-	< 0.01

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Columns (1)–(2) show results for import competition from China over 2001-07; Columns (3)–(4) show results for import competition from China over 1991-95. Columns (1) and (3) report OLS estimates; Columns (2) and (4) report IV estimates. ^{a} and ^{b} indicate significance at the 1 and 5 percent levels, respectively.

baseline analysis of Table 1 we consider the growth in imports from China over the whole period, thus accounting for both dynamics. In Table 2 we focus separately on two different sub-periods. Specifically, in Columns (1)–(2) we consider the growth in imports between 1991 and 1995, thus before parents' income is measured. Then, in Columns (3)–(4) we measure the growth in imports between 2001 and 2007, thus after parents' income has been measured and educational choices have been made. The estimated effects are negative and statistically significant in both cases, with similar magnitudes. Specifically, one standard deviation increase in import competition over 1991-1995 reduces absolute upward mobility by 0.39 of a standard deviation, versus 0.44 for the 2001–2007 period.

3.2 *Robustness Checks and Extensions*

Other sources of imports In Table 3, we focus on import competition from alternative sources. Specifically, in Columns (1)–(2) we consider the change in imports from all trading partners, over 1991-2007; in Columns (3)–(4) we focus on imports from a group of 52 low-income countries, as identified by Bernard, Jensen, and Schott (2006), over 1991-2007; in Columns (5)–(6) we focus on the change in imports from Mexico over 1993-2007, thus in correspondence with the establishment of NAFTA. Import exposure is always computed as outlined in equation (2), changing the import figures across specifications. The same approach is followed for the construction of the instrumental variables, according to equation (3). Specifically, imports from all trading partners are instrumented using their global exports, excluding exports to the U.S., as in Hummels et al. (2014) and Colantone, Crino, and Ogliari (2019). Imports from low-income countries and from Mexico are instrumented using their exports to the same set of eight high-income countries utilized by Autor, Dorn, and Hanson (2013) for Chinese imports.

All the estimated coefficients on import exposure are negative and precisely estimated, and somewhat larger in absolute value in the IV regressions compared to the OLS ones. This evidence suggests that the negative effect of trade exposure on absolute upward mobility is not specific to Chinese imports but extends to other sources of imports. Having said that, we prefer to focus on Chinese import exposure as a baseline, as China is the context in which the role of exogenous supply shocks over the sample period is more pronounced, thus providing a cleaner setup for the instrumental variables approach.

Table 3: Other Sources of Imports

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Absolute upward income mobility					
Exposure to All imports '91-'07	-0.021^{a}	-0.030^{a}				
	(0.006)	(0.008)				
Exposure to Low income imports '91-'07			-0.223^{a}	-0.336^{a}		
			(0.066)	(0.116)		
Exposure to Mexican imports '93-'07					-0.077^{a}	-0.142^{a}
					(0.027)	(0.040)
Gini coefficient	-0.494^{a}	-0.500^{a}	-0.486^{a}	-0.489^{a}	-0.481^{a}	-0.483^{a}
	(0.069)	(0.068)	(0.071)	(0.071)	(0.070)	(0.069)
Estimation	OLS	IV	OLS	IV	OLS	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	693	693	693	693	693	693
R-squared	0.43	-	0.42	-	0.41	-
First-Stage Results						
Exports to other high income countries	-	0.661^{a}	-	0.997^{a}	-	6.563^{a}
	-	(0.052)	-	(0.205)	-	(1.127)
Kleibergen-Paap F-Statistic	-	158.90	-	23.60	-	33.93
Anderson-Rubin p-value	-	< 0.01	-	0.0165	-	< 0.01

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Columns (1)–(2) show results for import competition from all countries over 1991-2007; Columns (3)–(4) report results for import competition from low income countries over 1991-2007; Columns (5)–(6) show results for import competition from Mexico over 1993-2007. Columns (1), (3), and (5) report OLS estimates; Columns (2), (4), and (6) report IV estimates. ^{a} indicates significance at the 1 percent level.

Controls for initial characteristics of commuting zones In Table 4 we augment the baseline IV specification of Column (4) in Table 1 with several controls for initial characteristics of commuting zones, as in the analysis by Acemoglu and Restrepo (2020). All controls are measured in 1990. In particular, in all columns we control for the employment share in manufacturing. In Column (2) we include a control for the offshorability index. In Column (3) we control for the share of employment in routine jobs. In Column (4) we include the following demographic characteristics: log of population size; share of females out of total population; share of over 65 years old; shares of population with no college, some college, college or professional degree, and masters or doctoral degree; and shares of whites, blacks, Hispanics, and Asians.

Table 4: Controlling for Initial Characteristics of Commuting Zones

	(1)	(2)	(3)	(4)
Dependent variable:	Absolute upward income mobility			
Exposure to Chinese imports '91-'07	-0.088^{a}	-0.057^{a}	-0.080^{a}	-0.043^{a}
	(0.027)	(0.022)	(0.024)	(0.013)
Manufacturing employment share	-0.141^{a}	-0.125^{a}	-0.110^{a}	-0.079^{a}
	(0.039)	(0.037)	(0.040)	(0.026)
Gini coefficient	-0.469^{a}	-0.464^{a}	-0.444^{a}	-0.257^{a}
	(0.068)	(0.067)	(0.074)	(0.051)
Offshorability index		-0.274^{b}		
		(0.139)		
Share of routine jobs employment			-4.099^{c}	
			(2.474)	
Demographic characteristics				Yes
Estimation	IV	IV	IV	IV
Area Fixed Effects	Yes	Yes	Yes	Yes
Observations	693	693	693	693
First-Stage Results				
Exports to other high income countries	0.941^{a}	1.098^{a}	0.929^{a}	0.932^{a}
	(0.169)	(0.207)	(0.174)	(0.184)
Kleibergen-Paap F-Statistic	31.17	28.19	28.58	25.65
Anderson-Rubin p-value	< 0.01	0.0107	< 0.01	< 0.01

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level; all columns report results from IV regressions. Demographic characteristics include: log of population size; share of females out of total population; share of over 65 years old; shares of population with no college, some college, college or professional degree, and masters or doctoral degree; and shares of whites, blacks, Hispanics, and Asians. ^{a}, ^{b} and ^{c} indicate significance at the 1, 5, and 10 percent levels, respectively.

The coefficient on exposure to Chinese imports is negative and precisely estimated across the board. At the same time, a higher initial share of employment in manufacturing is associated with lower mobility. Taken together, these results suggest that, conditional on the initial level of inequality: (i) overall exposure to structural transformation, as captured by the initial manufacturing share, is significantly related to reduced intergenerational income mobility; and (ii) the trade shock has a further specific negative impact on intergenerational income mobility. These two mechanisms are explored in the theoretical framework presented in Section 4.

Historical patterns of intergenerational mobility in the U.S. Intergenerational mobility may exhibit persistent patterns of geographic variation. To allow for that, in Table 5 we augment the baseline analysis of Table 1 by adding a control for historical mobility at the commuting zone level. Specifically, we employ the measure of upward mobility provided by Derenoncourt (2022), which is defined as the percentage of 14- to 18-year-old boys, and 14- to 16-year-old girls, who had a minimum of 9 years of schooling from households where the most educated parent had 5 to 8 years of schooling. This is measured in 1940.[11] While educational upward mobility is not the same as income mobility, it certainly provides a meaningful proxy for it. The inclusion of this control leaves our estimates on import exposure essentially unaffected. Moreover, the estimated coefficients on historical mobility are close to zero and mostly insignificant, pointing to a lack of strong persistence in mobility, in line with available evidence by Tan (2023).

Table 5: Controlling for historical mobility

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Absolute upward income mobility					
Exposure to Chinese imports '91-'07	-0.028^b	-0.098^a	-0.032^b	-0.108^a	-0.032^b	-0.091^a
	(0.013)	(0.028)	(0.014)	(0.027)	(0.014)	(0.030)
Historical measure of upward mobility in 1940	0.015^c	0.011	0.007	0.002	0.007	0.003
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)
Gini coefficient	-0.479^a	-0.487^a				
	(0.069)	(0.070)				
Gini bottom 99%			-0.593^a	-0.622^a		
			(0.082)	(0.081)		
Top 1% income share			-0.146^a	-0.138^a		
			(0.026)	(0.027)		
Share of households in middle class (p25-75)					0.595^a	0.611^a
					(0.103)	(0.098)
Estimation	OLS	IV	OLS	IV	OLS	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	692	692	692	692	692	692
R-squared	0.427	-	0.479	-	0.496	-
First-Stage Results						
Kleibergen-Paap F-Statistic	-	36.47	-	35.31	-	37.47
Anderson-Rubin p-value	-	< 0.01	-	< 0.01	-	< 0.01

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. With respect to the baseline analysis, we drop one commuting zone (28602, in Kansas) due to lack of data. Columns (1), (3), and (5) report OLS estimates; Columns (2), (4), and (6) report IV estimates. ^{a}, ^{b} and ^{c} indicate significance at the 1, 5 and 10 percent levels, respectively.

[11] Derenoncourt (2022) shows that historical migration shocks have resulted in lower upward mobility in the Northern part of the U.S., which is often associated with persistent segregation.

Other socio-demographic controls In Table 6 we augment the baseline IV specification of Column (4) in Table 1 with a battery of controls for socio-demographic characteristics of commuting zones. These are sourced from Chetty et al. (2014), who identify them as significant correlates of upward income mobility.[12] Specifically, we employ: the share of black residential population; the teenage labor-force participation rate; the share of single mothers from the 2000 US Census; the social capital index measured in 1990 by Rupasingha and Goetz (2008); the high-school dropout rate; income-adjusted students' test scores; and the fraction of workers whose commuting time is shorter than 15 minutes.[13] Our baseline evidence on the effect of import competition is robust to including these additional controls, notwithstanding the fact that some of them may be already post-treatment with respect to trade exposure.

Table 6: Controlling for Socio-demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Absolute upward income mobility								
Exposure to Chinese imports '91-'07	-0.103^a	-0.092^a	-0.079^a	-0.092^a	-0.085^a	-0.087^a	-0.088^a	-0.056^a	-0.049^a
	(0.029)	(0.023)	(0.025)	(0.020)	(0.027)	(0.026)	(0.025)	(0.018)	(0.014)
Gini coefficient	-0.490^a	-0.358^a	-0.384^a	-0.195^a	-0.381^a	-0.367^a	-0.317^a	-0.246^a	0.013
	(0.071)	(0.064)	(0.058)	(0.041)	(0.053)	(0.077)	(0.068)	(0.065)	(0.043)
Fraction of black population		Yes							Yes
Teenage labor force participation rate			Yes						Yes
Fraction of children with single mother				Yes					Yes
Social capital index					Yes				Yes
High school dropout rate						Yes			Yes
Test score percentiles							Yes		Yes
Fraction with commuting time < 15min								Yes	Yes
Estimation	IV	IV	IV	IV	IV	IV	IV	IV	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	693	693	693	693	693	580	692	693	579
First-Stage Results									
Exports to other high income countries	0.938^a	0.939^a	0.934^a	0.939^a	0.939^a	1.138^a	0.941^a	0.950^a	1.170^a
	(0.154)	(0.155)	(0.155)	(0.153)	(0.158)	(0.123)	(0.156)	(0.173)	(0.134)
Kleibergen-Paap F-Statistic	37.26	36.90	36.39	37.51	35.15	85.06	36.28	30.30	75.80
Anderson-Rubin p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level; all columns report results from IV regressions. The drop in observations in columns (6), (7), and (9) is due to missing data on the controls. ^{a} indicates significance at the 1 percent level.

Additional analyses In Table A.1 of the Online Appendix we replicate our baseline analysis using as a dependent variable relative income mobility (measured as rank-rank correlation) instead of absolute upward income mobility. Our results are consistent with the main evidence. Specifically, we find that import competition increases the rank-rank correlation between children's and parents' income, thus reducing income mobility. Finally, in Table A.2 of the Online

[12] All controls display a correlation with upward income mobility of around 0.6 or higher (see Figure 8 of Chetty et al., 2014).

[13] Chetty et al. (2014) provide details on all these variables in Section G of their Online Appendix.

Appendix we show that our baseline results are robust to including fixed effects for US Census divisions instead of US Census regions.

4 Theoretical Framework

In this section we present a parsimonious quantitative spatial model in general equilibrium that rationalizes the evidence discussed in the previous section. The main mechanism we build in the model is a localized effect that makes it more likely for young individuals born in a given location to select the dominant local industries as sectors of future employment. This may be due to localized externalities that promote specialized learning and training or more general local traditions and norms that foster path dependency in the footsteps of previous generations.[14] If the dominant local industries are then hit by an adverse trade shock, path dependency may lock the newer generations in situations in which they underperform in terms of income with respect to older generations because of limited sectoral and geographical mobility determined by choices made earlier in their life. That would be the case, for instance, if young individuals born in a place specialized in textiles were more likely to choose the textiles industry as their sector of future employment thanks to the transmission of specialized knowledge from their parents, and that industry subsequently suffered from import competition. Subsections 4.1 to 4.3 formalize this idea within the framework of a full-fledged spatial model, then Subsections 4.4 and 4.5 derive the implied measure of upward income mobility and its response to trade shocks. Section B of the Online Appendix presents a more detailed exposition of the model.

4.1 *Basic Setup*

Geography and endowments The world economy is made of two countries: the home and the foreign. The home country comprises a discrete number of locations and the foreign country consists of a single location. We let $\mathcal{N}$ denote the set of locations in the entire economy and $\mathcal{H}$ denote the set of locations in the home country. Location $i \in \mathcal{N}$ is endowed with an amount T_i of land that is fixed over time. Time is discrete. At the generic time t the economy is inhabited by two overlapping generations of equal size $\bar{L}$: the old born at time $t-1$ and the young born at time 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. These can be employed together with land in two sectors, manufacturing (M) and services (S), with different degrees of national and international tradability. During the first period, young workers decide in which location to live and in which sector to work when old,

[14] While we keep the mechanism in reduced form for now, in Section 6 we will show how to derive it from forward-looking educational choices when the local supply of education is financed from local income.

thus potentially giving rise to intergenerational changes in employment across locations and sectors.

Production and trade In each sector there are final good producers and intermediate good producers. Final good producers supply local consumption goods using sector-specific intermediate goods. The production technology of final good producers is CES with sector-specific constant elasticity of substitution. Intermediate goods are produced using labor and land exploiting a Cobb-Douglas production technology with localized external economies of scale. All markets are perfectly competitive. The cost shares of labor and land in sector j are β_j and $1-\beta_j$ respectively, and the overall productivity in the local economy is a function of fundamental productivity and the size of employment. These features are summarized by the unit production cost for intermediate goods:

$$c_{nt}^{j} = \frac{\left(w_{nt}^{j}\right)^{\beta_j}\left(r_{nt}\right)^{1-\beta_j}}{a_{nt}^{j} {L_{nt}^{j}}^{\gamma_j}}, \tag{5}$$

where w_{nt}^{j} is the sector-specific wage, r_{nt} is the land rent (which is the same for both sectors), γ_j is a parameter regulating the scale economies, and a_{nt}^{j} is fundamental productivity. Trade in intermediate goods is hampered by transport frictions in the form of iceberg trade costs: $\tau_{int}^{j} > 1$ units have to be shipped between location i and n in sector j for one unit to reach a destination. In the wake of Eaton and Kortum (2002), idiosyncratic productivity shocks for an individual intermediate producer follow a Fréchet distribution with shape parameter ϵ_j in sector j. Then, final good producers in location i import their intermediate goods produced in location n with probability:

$$\pi_{int}^{j} = \Gamma^{j} \left(\frac{\tau_{int}^{j} c_{nt}^{j}}{p_{it}^{j}} \right)^{-\epsilon_j}, \tag{6}$$

where p_{it}^{j} is price of the final good in location i and sector j while Γ^{j} is a constant.

4.2 *Workers*

We let worker ω of generation t refer to an individual born at time $t-1$ who supplies labor at time t. The lifetime utility of worker ω of generation t who lived in location i in period $t-1$ and is employed in location n and sector j at time t is given by:

$$\ln U_{int}^{j}(\omega) = \ln V(\{Q_{nt}^{j}(\omega)\}) - \ln D_{int} + \ln v_{nt}(\omega) + \ln z_{it}^{j}(\omega),$$

where $\{Q_{nt}^{j}(\omega)\}$ is the worker's consumption bundle and D_{int} is a relocation cost incurred in moving from location i to n. We use $V(\cdot)$ to denote the subutility from consumption.

There are two idiosyncratic taste shocks $\ln v_{nt}(\omega)$ and $\ln z^j_{it}(\omega)$ that affect the sector and location choices of a worker, respectively. The first type of shock affects the worker's satisfaction in living in location n when old, and we assume that the shock $\{v_{nt}(\omega)\}$ follows a Fréchet distribution with a shape parameter $\alpha \in (1, \infty)$. The second type of shock $\{z^j_{it}(\omega)\}$ affects the worker's satisfaction in choosing sectoral occupation j when young in location i. The number of taste shocks for this choice follows the sector-specific Poisson distribution:

$$m^j_{it}(\omega) \sim \frac{(\mathcal{B}^j_{it-1})^m e^{-\mathcal{B}^j_{it-1}}}{m!}, \quad \ln \mathcal{B}^j_{it-1} = \psi \ln L^j_{it-1}, \quad \psi > 0 \tag{7}$$

and each taste shock $\{z^j_{it}(\omega)\}$ is independently drawn from the Pareto distribution:

$$1 - (z/z_{\min})^{-\eta}, \quad \eta > 1 \tag{8}$$

The presence of the local exposure effect $\mathcal{B}^j_{it-1}$ can be microfounded in terms of job search during the young period (Takeda 2022). The expected number of arrivals of taste shocks and their variance depends on the location when young. In particular, there is a positive externality from the local production structure to sectoral preferences when young. Individuals born in manufacturing locations are more likely to prefer jobs in the manufacturing sector, whereas those born in services cities are more likely to be attracted by the service sector.[15]

The subutility $V(\cdot)$ is assumed to be non-homothetic CES, with sectoral expenditure shares given by:

$$\mu_{j|nj't} = \left(p^j_{nt}\right)^{1-\sigma} \left(P^{j'}_{nt}\right)^{\sigma-\theta_j} \left(Y^{j'}_{nt}\right)^{\theta_j - 1}, \quad j, j' \in \{M, S\} \tag{9}$$

where p^j_{nt} is the price of consumption goods, $P^{j'}_{nt}$ is a worker-specific aggregate price index, and $Y^{j'}_{nt}$ is income. The parameter of elasticity of substitution is given by $\sigma < 1$. Non-homotheticity materializes as long as θ_j differs from one, in which case θ_j captures the difference in the slope of the Engel curve.

4.3 *General Equilibrium*

A worker's decisions are sequential. Anticipating future prices and taste shocks, the worker first chooses the sector in which to work; then, conditional on the sector's choice, the worker chooses the location where to find a job.

To characterize the equilibrium, we start with the transition probabilities for workers between locations and sectors. First, the probability that a worker born in location i at time $t-1$ ends up working in location n at time t conditional on choosing sector j is:

$$\lambda^j_{nit} = \left(\frac{Y^j_{nt}/P^j_{nt}}{D_{nit}\bar{U}^j_{it}}\right)^{\alpha}, \quad i, n \in \mathcal{N}, \tag{10}$$

[15] See Section 6 for a micro-founded model of educational choice leading to this outcome.

where $\bar{U}^j_{it}$ is expected utility conditional on job choice j for a worker born in location i. The probability that a worker born in location i moves location n is an increasing function of real income in the destination (Y^j_{nt}/P^j_{nt}) and a decreasing function of bilateral migration costs (D_{nit}). The parameter α also corresponds to migration elasticity.

Second, the probability that a worker born in location i at time $t-1$ chooses sector j is given by:

$$\kappa^j_{it} = \left(L^j_{it-1}\right)^{\psi} \left(\frac{\bar{U}^j_{it}}{\Xi_{it}}\right)^{\eta}, \quad j \in \{M, S\} \tag{11}$$

where Ξ_{it} is the ex-ante average utility of a worker born in location i. The probability is higher when location i has more workers of the previous generation (L^j_{it-1}) in sector j and this sector exhibits higher expected utility ($\bar{U}^j_{it}$). The parameter η captures the labor supply elasticity while ψ regulates the degree of persistence in the sectoral choices in location i.

Given those two probabilities, trade in intermediate goods implies that the labor market clearing condition in location n for sector $j \in \{M, S\}$ can be stated as:

$$\sum_{i\in\mathcal{N}} \lambda^j_{nit}\kappa^j_{it}L_{it-1} = \frac{\beta_j}{w^j_{nt}} \sum_{i\in\mathcal{N}} \pi^j_{int} \left[\sum_{j'} \mu_{j|ij't} Y^{j'}_{it} \left(\sum_{n\in\mathcal{N}} \lambda^{j'}_{int}\kappa^{j'}_{nt}L_{nt-1}\right)\right], \quad n \in \mathcal{N} \tag{12}$$

The left-hand side is the labor supply of generation t in location n and sector j. The right-hand side is labor demanded for the production of intermediate goods, which is determined by the expenditure share of workers ($\mu_{j|ij't}$), trade patterns (π^j_{int}) and the labor share in production (β_j).

Next, in any given location, land is assumed to be owned by local workers in equal proportions so that workers of generation t in location n receive the rents accruing to land in period t. Total income per worker employed in sector j of location n then evaluates to:

$$Y^j_{nt} = w^j_{nt} + \frac{r_{nt}T_n}{L_{nt}}, \tag{13}$$

where total land rents ($r_{nt}T_n$) are equally distributed among workers.

Lastly, land market clearing requires:

$$r_{nt}T_n = \sum_j \left[\frac{1-\beta_j}{\beta_j} w^j_{nt} \left(\sum_{i\in\mathcal{N}} \lambda^j_{nit}\kappa^j_{it}L_{it-1}\right)\right], \quad n \in \mathcal{N}, \tag{14}$$

where the right-hand side is land demanded for the production of intermediate goods and $1-\beta_j$ is the land share in production.

Wrapping up, the equilibrium spatial distribution of economic activities in a country is determined by: (i) preference parameters (σ, θ_M, θ_S), production and productivity parameters (β_M, β_S, ϵ_M, ϵ_S, γ_M, γ_S), and idiosyncratic shocks related to workers' location and sector choices

(α, η, ψ); (ii) fundamental location characteristics (T_n, a^M_{nt}, a^S_{nt}); (iii) trade and migration costs ($\tau^M_{int}, \tau^S_{int}, D_{int}$); (iv) the initial distribution of workers across locations (L^M_{n0}, L^S_{n0}); and (v) total population $\bar{L}$.

Given the model parameters and exogenous primitives, the equilibrium within a country is then characterized by the vectors of wages $\{w^M_{nt}, w^S_{nt}\}^T_{t=0}$, the vector of land prices $\{r_{nt}\}^T_{t=0}$, and the employment distribution across sectors and locations $\{L^M_{nt}, L^S_{nt}\}^T_{t=1}$ that solve: (i) workers' utility maximization implying expenditure share (9); (ii) workers' location choice according to equation (10) and their sector choice according to equation (11); (iii) the labor market clearing conditions (12); (iv) the land market clearing conditions (14); and (v) the distribution rule of land rents among workers across locations according to equation (13). The proof that such equilibrium exists can be found in the Online Appendix B.

4.4 *Intergenerational Income Mobility*

To obtain the model's equivalent of the definition of workers' upward income mobility used in the empirical part, we consider the mass probability function of local income. Aggregating across sectors and home locations at time t, the mass of workers employed in location i in Home ($\mathcal{H}$) with income below $Y^j_{it}(\omega)$ is given by:

$$\mathcal{R}^j_{it}(\omega) \equiv \sum_{n\in\mathcal{H}} \sum_{j'} \mathbb{I}\left[Y^{j'}_{nt} \leq Y^j_{it}(\omega)\right] \frac{f^{j'}_{nt} L_{nt}}{L_{\mathcal{H}t}}, \quad i \in \mathcal{H},\ j \in \{M, S\}, \tag{15}$$

where $f^{j'}_{nt}$ is share of workers in sector j' in location n, $L_{nt}/L_{\mathcal{H}t}$ is home population share of location n, and $\mathbb{I}\left[Y^{j'}_{nt} \leq Y^j_{it}(\omega)\right]$ is an indicator that income of workers in sector j' and location n is below those in sector j and location i. In other words, expression (15) is the percentile of worker ω in the income distribution of the home country when working in sector j and location i.

Our baseline measure of upward income mobility between two generations is the ratio of the average income percentile of generation t from origin i to that of generation $t-1$ working in location i as given by:

$$\Omega_{it} \equiv \frac{\mathbb{E}\left[\mathcal{R}^j_{nt}(\omega) \mid \{\kappa^j_{it}\}, \{\lambda^j_{nit}\}\right]}{\mathbb{E}\left[\mathcal{R}^j_{it-1}(\omega)\right]} = \sum_j \left[\kappa^j_{it} \left(\sum_{n\in\mathcal{H}} \frac{\lambda^j_{nit} \mathcal{R}^j_{nt}}{\sum_{j'} f^{j'}_{it-1} \mathcal{R}^{j'}_{it-1}}\right)\right], \quad i \in \mathcal{H} \tag{16}$$

Intuitively, expression (16) captures what a new generation born in a given location achieves on average (wherever it ends up residing) relative to what the previous generation of residents in that location achieved on average. The larger the value of Ω_{it}, the higher the upward income mobility between generations.

4.5 *Exposure to the Trade Shock and Intergenerational Income Mobility*

We now consider a trade shock that affects a specific industry within the home country. In the context of the China shock, structural reforms in the Chinese economy enhanced the productivity of exporting industries within the manufacturing sector, leading to a surge in imports from China to the U.S. and a subsequent contraction of the U.S. manufacturing sector (Autor, Dorn, and Hanson 2013). In our setup, this shock is isomorphic to a negative shock to the productivity of the manufacturing sector in the home country, which unambiguously leads to its contraction. Accordingly, we model the trade shock as a drop in home manufacturing productivity occurring in period $t-1$. How does this affect the upward income mobility of workers of generation t from manufacturing-intensive locations?

The predicted change in the upward mobility (16) of generation t relative to generation $t-1$ can be expressed as:

$$\widehat{\Omega}_{it} = \sum_{j} \frac{\Theta^{\mathbb{K}}_{ijt} \left[\frac{(\widehat{W}^{j}_{it})^{\eta} (\widehat{\lambda}^{j}_{iit})^{-\eta/\alpha}}{\sum_{j'} \kappa^{j'}_{it} (\widehat{W}^{j'}_{it})^{\eta} (\widehat{\lambda}^{j'}_{iit})^{-\eta/\alpha}} \right] \widehat{\lambda}^{j}_{iit} \left[\sum_{n \in \mathcal{N}} \Theta^{\mathbb{M}}_{nijt} \left(\frac{\widehat{W}^{j}_{nt}}{\widehat{W}^{j}_{it}} \right)^{\alpha} \widehat{\mathcal{R}}^{j}_{nt} \right]}{\sum_{j} \Theta^{\mathbb{F}}_{ijt-1} \widehat{\mathcal{R}}^{j}_{it-1}}, \tag{17}$$

where $\widehat{W}^{j}_{it}$ is the change in the real income of workers ($W^{j}_{it} \equiv Y^{j}_{it}/P^{j}_{it}$) in location i and sector j; $\widehat{\lambda}^{j}_{iit}$ is the change of workers' probability of not migrating conditional on working in sector j; and $\widehat{\mathcal{R}}^{j}_{it}$ is the change in income percentile for workers of generation t in location i and sector j.

The expression (17) also features three probabilities that regulate the relative importance of different channels of adjustment: $\Theta^{\mathbb{F}}_{ijt-1}$ captures the contribution of sector j in the average income percentile for workers of generation $t-1$ in location i before the shock; $\Theta^{\mathbb{K}}_{ijt}$ captures the contribution of sector j for upward income mobility of generation t from location i in the baseline equilibrium; $\Theta^{\mathbb{M}}_{nijt}$ captures the baseline migration opportunity of workers of generation t in location i conditional on choosing sector j. A higher value of $\Theta^{\mathbb{M}}_{nijt}$ implies that workers have more opportunity to migrate to prosperous locations for the sector of their choice.[16]

The trade shock affects upward income mobility through four channels. First of all, in the denominator of equation (17), the shock lowers the average income percentile for workers of generation $t-1$ in locations with a large share of employment in manufacturing sector.

[16]Specifically, we define: $\Theta^{\mathbb{F}}_{ijt-1} = \frac{L^{j}_{it-1}\mathcal{R}^{j}_{it-1}}{\sum_{j'} L^{j'}_{it-1}\mathcal{R}^{j'}_{it-1}}$ as the contribution of sector j in the average income percentile for workers of generation $t-1$ in location i; $\Theta^{\mathbb{M}}_{nijt} = \frac{\lambda^{j}_{nit}\mathcal{R}^{j}_{nt}}{\sum_{n'} \lambda^{j}_{n'it}\mathcal{R}^{j}_{n't}}$ as the migration opportunity, and $\Theta^{\mathbb{K}}_{ijt} = \frac{\kappa^{j}_{it}\lambda^{j}_{iit}\mathcal{R}^{j}_{it}\left(\Theta^{\mathbb{M}}_{iijt}\right)^{-1}}{\sum_{j'} \kappa^{j'}_{it}\lambda^{j'}_{iit}\mathcal{R}^{j'}_{it}\left(\Theta^{\mathbb{M}}_{iij't}\right)^{-1}}$ as the contribution of sector j in determining the upward income mobility of workers of generation t in the baseline.

The other three channels have impacts on generation t. As for the second channel, the trade shock lowers the real income (W_{it}^{j}) and the non-migration probability (λ_{iit}^{j}) of workers of generation t in the manufacturing sector *ceteris paribus*. The former effect is relatively strong, while the latter is weak for manufacturing-intensive locations. This is because workers of generation t still exhibit a high likelihood of choosing a job in the manufacturing sector due to historical exposure to that sector, and they are less likely to emigrate to other places with relatively low productivity in manufacturing. These effects together capture the exposure of workers to the trade shock, which is summarized by the term: $\frac{(\widehat{W}_{it}^{j})^{\eta}(\widehat{\lambda}_{iit}^{j})^{-\eta/\alpha}}{\sum_{j'}\kappa_{it}^{j'}(\widehat{W}_{it}^{j'})^{\eta}(\widehat{\lambda}_{iit}^{j'})^{-\eta/\alpha}}$ in equation (17).

The third channel is the direct effect of migration given by $\widehat{\lambda}_{iit}^{j}$, which regulates the change in the attractiveness of location i for workers once there is a productivity shock in sector j. Lower attractiveness of the location is associated with lower intergenerational mobility.

The fourth and last channel, captured by $\sum_n \Theta_{nijt}^{\mathbb{M}}(\widehat{W}_{nt}^{j}/\widehat{W}_{it}^{j})^{\alpha}\widehat{\mathcal{R}}_{nt}^{j}$, works through the change in location i's labor market access in the home economy. Conditional on working in the manufacturing sector, less emigration to other service-intensive locations *ex ante* leads to lower gains in labor market access after the shock. Therefore, workers from manufacturing-intensive locations are more likely to show lower upward income mobility.

Taken together, all these channels affect the upward income mobility of workers of generation t with weights determined by the local ex-ante manufacturing intensity as measured by $(\Theta_{ijt}^{\mathbb{K}})$. Intuitively, if locations are manufacturing intensive to start with, the negative effects in the numerator of equation (17) are strong enough to decrease their workers' opportunity to climb up the income ladder compared to the preceding generation. To better highlight how the trade shock affects upward income mobility in line with our empirical evidence, the next section solves and simulates the model numerically.

5 Theory with Numbers

In this section we parametrize the model and numerically solve for the equilibrium. There are two motivations for our numerical solutions. The first is to flash out the equilibrium relationship between structural transformation and the upward mobility of workers, highlighting the dynamics of equilibrium variables. The second is to visualize the impact of a trade shock on the spatial patterns of upward income mobility in the home country.

Subsection 5.1 describes the specific version of the model that we use for our numerical analysis.[17] Subsection 5.2 presents the benchmark patterns of upward income mobility. Subsection 5.3 shows how a trade shock impacts upward income mobility differently across locations depend-

[17] The stylized economy in this paper is similar to the setup in Desmet and Rossi-Hansberg (2014).

ing on their initial manufacturing intensity. Specifically, we suppose that a positive productivity shock in the foreign country occurs, leading to an increase in its manufacturing exports to the home country. By comparing the model's equilibrium before and after such trade shock, we assess the effects of the shock on the spatial distribution of economic activities and intergenerational mobility.

5.1 *A Dynamic Spatial Economy with Two Countries and Two Sectors*

Setup There are two countries in the economy: the home country and the foreign country. We interpret the home country as corresponding to the U.S. motivated by our empirical findings, and the foreign country as corresponding to other countries, including China. The home country consists of 200 discrete locations evenly spaced along the closed interval $[0, 1]$. The foreign country consists of a single location. The distance between the foreign country and all locations in the home country is the same and is normalized to one. We turn off the spatial variation in land endowment across locations in the home country. The foreign country is large in terms of land endowment, and we assume that the total land endowment in the home country is 10 percent of that in the foreign country. There are two sectors: manufacturing ($\mathcal{M}$) and services ($\mathcal{S}$). To focus on the endogenous drivers of structural transformation in the baseline economy, we mostly impose symmetric parameter values for the two sectors, as described below.

Parametrization Table 7 provides a summary of the model parameters, their baseline values, and their sources, which we discuss in turn.

The demand system has three parameters. We set the elasticity of substitution between manufacturing and service sectors to 0.5 following the macroeconomic literature on structural transformation. This ensures complementarity between manufacturing and services in consumption. We assign different slopes of the Engel curve to the two sectors by normalizing θ_M to 1 for manufacturing and setting θ_S to 1.2 for services, which is in the middle of estimates from Table III in Comin, Lashkari, and Mestieri (2021). This implies that the service sector's expenditure share increases with real income.

Turning to production, the input share of labor is set to 0.6 for both the manufacturing and the service sectors, which falls within the range of various estimates provided by the literature. We set the shape parameter of the Fréchet productivity distribution of intermediates to 6 for both manufacturing and services. This is the middle value of the range of estimates obtained from gravity equations in the trade literature. We set the scale elasticity of overall productivity to employment size at 0.05 as a benchmark value for both manufacturing and services.

There are three parameters regarding workers' choices. The first is the shape parameter of the Fréchet distribution of idiosyncratic taste shocks in the location choice (α). Since this parameter

Table 7: Parameters

Parameter	Source and Comments
1. **Demand**: $\mu_{j\|nj't} = \left(p^j_{nt}\right)^{1-\sigma}\left(P^{j'}_{nt}\right)^{\sigma-\theta_j}\left(Y^{j'}_{nt}\right)^{\theta_j-1}$	
$\sigma = 0.5$	Elasticity of substitution between industries
$\theta_M = 1, \quad \theta_S = 1.2$	Sector specific non-homotheticity; Comin, Lashkari, and Mestieri (2021)
	θ_M for manufacturing sector; θ_S for service sector
2. **Production**: Unit production cost is $(w^j_{nt})^{\beta_j}(r_{nt})^{1-\beta_j}$	
$\beta_M = \beta_S = 0.6$	Share of labor in production for both sectors
3. **Productivity**: Idiosyncratic productivity drawn from $\exp(-x^{-\epsilon_j})$; Overall productivity is $a^j_{nt}(L^j_{nt})^{\gamma_j}$	
$\epsilon_M = \epsilon_S = 6$	Trade elasticity from the gravity estimates in literature
$\gamma_M = \gamma_S = 0.05$	Local externalities: agglomeration in productivity
4. **Workers' Choice**: $\ln \mathcal{B}^j_{it-1} = \psi \ln L^j_{it-1}$; $\quad \Psi(z) = 1 - (z/z_{\min})^{-\eta}$	
$\alpha = 1.5$	Migration elasticity; Fajgelbaum et al. (2019)
$\eta = 2.5$	Variation of taste shocks in sector choice; Takeda (2022)
$\psi = 0.8$	Local labor market exposure effect; Takeda (2022)
5. **Spatial frictions**: $\tau^j_{int} = \exp(\delta_j \text{dist}_{in})$; $D_{int} = \exp(d \cdot \mathbb{I}(i \neq n))$	
$\delta_M = \delta_S = 0.1$ (Home)	Trade cost elasticity in the domestic trade
$\delta_M = \delta_S = 0.25$ (Foreign)	Trade cost elasticity for foreign trade; Ramondo and Rodríguez-Clare (2013)
$d = 0.10$	Domestic migration cost when people change locations ($i \neq n$)
$d = 2.25$	Inter-country migration cost

Note: This table reports parameters in quantitative analysis. In each panel, the first row shows the functional form determined by parameters.

captures the elasticity of labor reallocation across different cities with respect to real income, we set the parameter to 1.5 following Fajgelbaum et al. (2019). The remaining parameters include the shape parameter of the Pareto distribution of the value of idiosyncratic taste shocks in the sector choice (η) and the elasticity of the average number of taste shocks to employment in the previous generation (ψ). We set these two parameters following the estimates in Takeda (2022): $\eta = 2.5$ and $\psi = 0.8$ respectively.

Finally, we parametrize migration and trade costs as follows. The migration costs within the home country are independent of geographic distances and we set the mobility cost from the origin such that workers lose around 10 percent of their utility when they relocate within the home country.[18] The migration cost to the foreign country is set sufficiently high to rationalize the low rate of inter-country migration. The bilateral trade cost takes the form $\tau^j_{int} = \exp(\delta_j \text{dist}_{in})$ with sector j's efficiency of transportation δ_j and geographical distance dist_{in}. Following Ramondo and Rodríguez-Clare (2013), we set $\delta_j = 0.25$ for inter-country trade. We suppose trade within the home country is less costly and set $\delta_j = 0.1$ for domestic trade.

[18] This implies that we assume away heterogeneity in migration costs for internal migration. The reason for this is twofold. First, there is no consensus in the literature on the functional form of bilateral migration costs in relation to distance within a country. Second, in a one-dimensional space such as ours, bilateral migration costs create an exogenous location advantage for the central place that is isomorphic to advantage in fundamental amenities.

Location fundamentals Fundamental productivity of the manufacturing sector (a_{nt}^{M}) exhibits differences across locations within the home country. The initial distribution of fundamental productivity for the manufacturing sector is assumed to reach its highest value in the center of the home country to avoid multiple equilibria given the parallel advantage centrality gives in terms of trade. In contrast, the initial level of the fundamental productivity for services is uniformly distributed across locations in the home country.[19] The initial fundamental productivity in the foreign country is set to the average of the home country in both sectors. Fundamental productivity grows uniformly at a constant rate across locations both in the home country and the foreign country. We also impose the same growth rate for manufacturing and services productivity in order to focus on the endogenous mechanisms of structural transformation through the consumption and sector choices of workers.[20] Lastly, we do not allow for any variation in fundamental amenities across locations in the economy.

5.2 *Upward Income Mobility in the Home Country*

We start by describing a baseline pre-shock dynamic equilibrium by simulating the model over 25 periods. For the initial period, we assume that the economy is in a steady state.

Figure 3 depicts the distribution of employment in the manufacturing sector of the home country. As expected, given the initial distribution of fundamental productivity and the advantage of centrality, employment in manufacturing exhibits a peak around the central location as shown by the top solid line. As time passes, fundamental productivity grows at a constant rate and, as preferences are non-homothetic, the economy undergoes structural transformation from manufacturing towards service.[21] Since the center of the home country has an advantage in fundamental productivity, agglomeration forces keep more manufacturing workers in the center relative to the edges of the home country.[22]

Figure 4 illustrates the relationship between workers' upward income mobility and the rate of structural transformation in the home country. The left panel of Figure 4 depicts the fitted line for the relationship between the model's measure of upward income mobility given in equation (16)

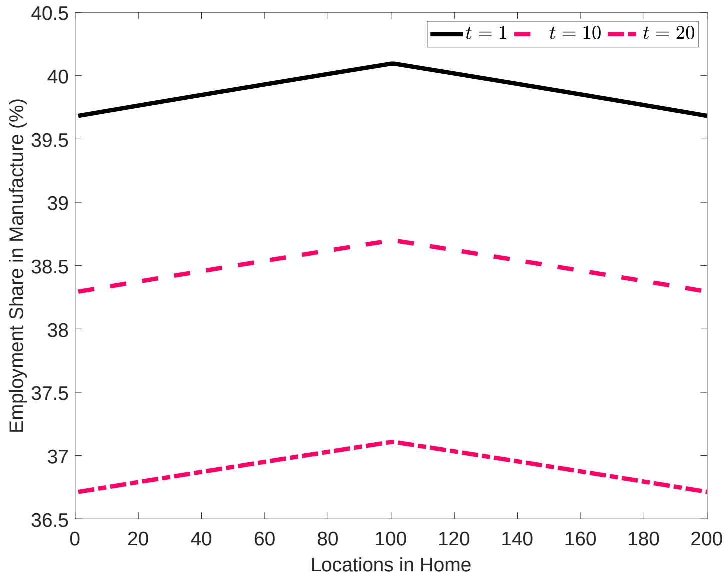
[19]If we assume a uniform distribution of fundamental productivity, potentially multiple equilibria arise where one sector is concentrated either in the central place or the edges. In our numerical solutions, the initial fundamental productivity for the manufacturing sector is 0.99 in the edges while 1.01 in the center of the home country. This rationalizes the concentration of manufacturing in the early period of the economy and eliminates the potential multiplicity of equilibria. The initial fundamental productivity of service sector exhibits uniform distribution at 0.25 across locations in the home country.

[20]Specifically, we assume that the growth rate of fundamental productivity is 5 percent every period for both manufacturing and services in the world.

[21]Productivity growth in both manufacturing and services leads to higher real income for workers in the home country and non-homotheticity in consumption causes a shift in demand from manufacturing to services. In Section C of the Online Appendix we also demonstrate that the pattern of structural transformation in the aggregate economy is consistent with the observed trend in the real economy.

[22]We also see that land rents are higher in the central location given its productivity advantage.

Figure 3: Distribution of Employment in the Home Country



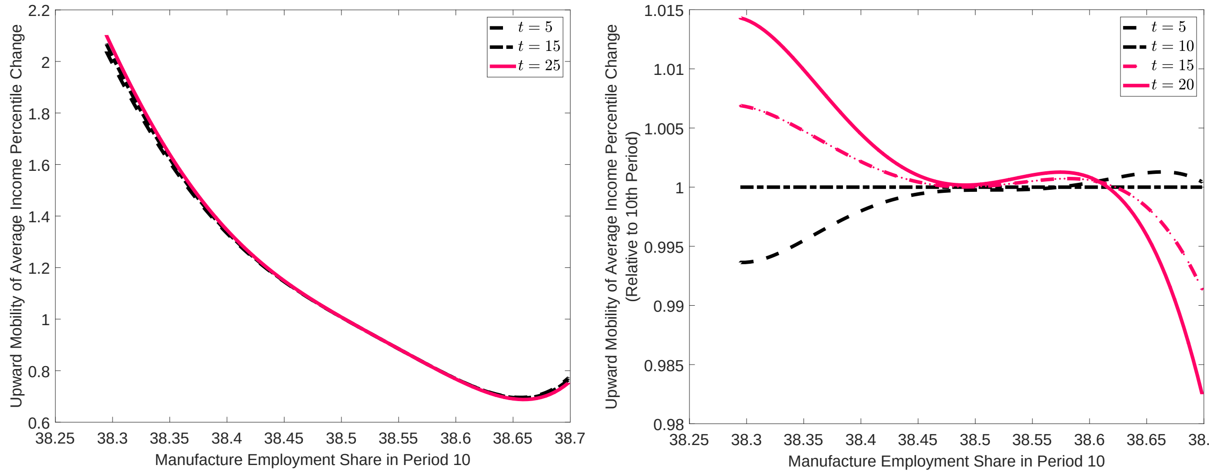
Note: Vertical axis shows employment share in manufacturing sector for each period; horizontal axis shows the index of locations in the home country. We show the fitted line across 200 locations in the home country for three periods: 1st, 10th, and 20th periods.

for workers from any particular location on the vertical axis and the location's employment share in the manufacturing sector in the 10th period on the horizontal axis. For all three generations represented, the upward income mobility of workers from locations with a small manufacturing employment share is relatively high. Theoretically, workers can achieve higher upward income mobility if they are more likely to choose the service sector as this exhibits higher relative wages in the home country due to structural transformation. Given the persistence of workers' sector choice in their birthplace, the expected income percentile for workers from locations with more employment in services in previous generations is high relative to locations with a large fraction of employment in manufacturing.[23]

Turning to the right panel of Figure 4, the change in the degree of upward income mobility over time exhibits variation across locations in the home country. Each line represents the fitted line for the relationship between upward income mobility relative to the 10th generation and the employment share of manufacturing sector in the 10th period. Locations with less structural transformation are associated with lower upward income mobility over time. The difference in la-

[23]Nonetheless, we also find a small reversal of the downward slope for locations with the highest concentration of manufacturing employment. Intuitively, the likelihood of workers choosing manufacturing is highest in these locations. With migration costs, those workers are more likely to remain in the location where the productivity of manufacturing is growing in relative terms through spillover and the land price is relatively high. Considering these joint phenomena, workers in locations with concentrated manufacturing regain their income mobility. This observation aligns with the historical pattern found in Tan (2023), indicating a higher level of mobility among individuals raised in industrial regions in the middle of the U.S.

Figure 4: Upward Income Mobility and Structural Transformation in the Home Country



(a) Pattern of Upward Income Mobility

(b) Change in Upward Income Mobility

Note: Left panel shows fitted lines of 200 locations in the home country for the relationship between upward income mobility of the 5th, 15th and 25th generations (vertical axis) and manufacturing employment share in the 10th period (horizontal axis). Right panel shows fitted lines of 200 locations in the home country for the relationship between upward income mobility of the 5th, 15th and 20th generations relative to the 10th generation (vertical axis) and manufacturing employment share in the 10th period (horizontal axis).

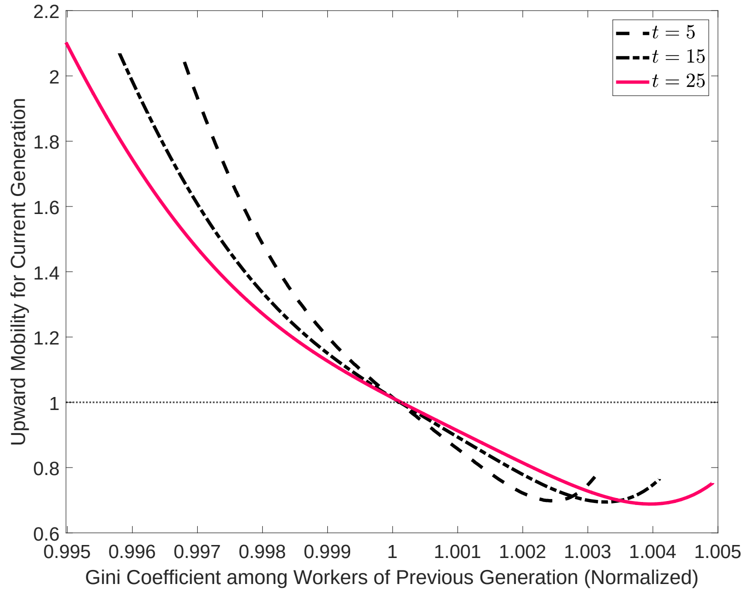
bor composition leads to disparity in income mobility through the persistence of workers' choices of sector and location, and structural transformation benefits workers in services-intensive locations.

Next, we investigate the relationship between income inequality and upward income mobility. Figure 5 illustrates the fitted line for locations in the home country, with the Gini coefficient among workers of the 4th, 14th and 24th generations on the horizontal axis and upward income mobility among workers of the 5th, 15th and 25th generations on the vertical axis. Our numerical solutions reveal the existence of a "Great Gatsby Curve". Intuitively, as structural transformation proceeds, the general equilibrium effects in the local labor market drive up the manufacturing sector's share of income relative to its share of employment in manufacturing-intensive locations. This leads to two consequences behind the relationship depicted in Figure 5. First, it implies large income inequality for locations with more employment in the manufacturing sector, as captured by the Gini coefficient. Second, workers from manufacturing-intensive locations are more likely to choose to work in manufacturing. Being less mobile conditional on their sectoral choice, these workers are limited in terms of upward income mobility.

5.3 *Trade Shock and Upward Income Mobility*

We are now in a position to investigate how trade shocks affect the upward income mobility of workers in the home country. To engineer a one-time import penetration shock specific to

Figure 5: Upward Income Mobility and Income Inequality in the Home Country



Note: Vertical axis shows upward income mobility for workers of the 5th, 10th and 25th generations; horizontal axis shows the normalized Gini coefficient among workers in each location for the 4th, 9th and 24th generations. We show the fitted lines across 200 locations in the home country.

manufacturing, we assume that the fundamental productivity of foreign manufacturing in the 11th period becomes twice as large as that in the 10th period. This is motivated by the calibration of the China shock in the quantitative trade literature (e.g., Caliendo, Dvorkin, and Parro 2019; Galle, Rodríguez-Clare, and Yi 2023). All other parameters remain unchanged. In particular, trade costs and the constant growth rate of fundamental productivity before and after the one-time trade shock are identical to the baseline without the trade shock. Due to import penetration, the trade shock induces a further decline in manufacturing employment in the home country, and the relative decline in manufacturing employment is larger in locations where the employment share of manufacturing sector is higher.[24]

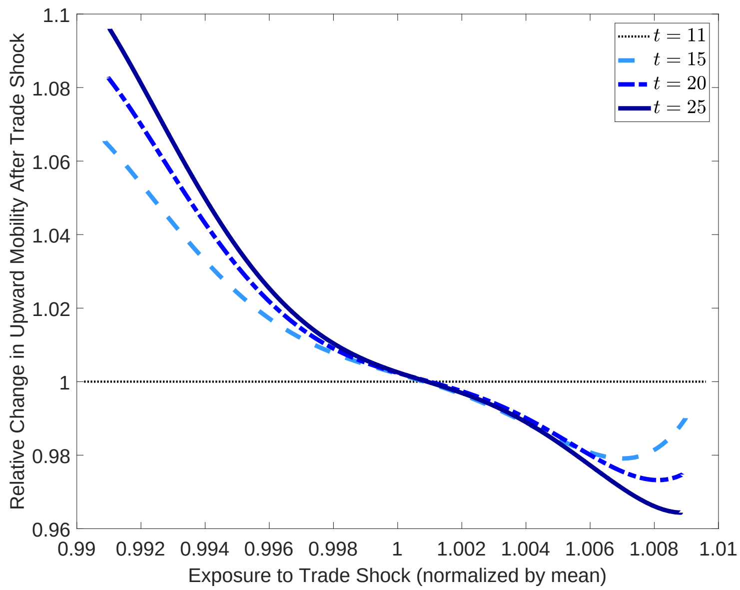
Our primary objective is to analyze the relationship between the degree of exposure to the trade shock and upward income mobility across locations in the home country. In Figure 6 the horizontal axis reports the weighted change in import value from the foreign country, using the initial employment composition of each location as weight, while the vertical axis reports the relative change in upward income mobility for workers from each location after the trade shock.[25] Each line depicts the change in upward income mobility relative to the 11th generation.

[24] In Figure C.1 of the Online Appendix, we show that structural transformation in the home country is accelerated by the trade shock, with more workers relocating from manufacturing to services. Within the home country, the rate of structural transformation is uneven. Figure C.2 of the Online Appendix shows that the impact of the trade shock varies by location given the initial level of structural transformation in the home country.

[25] Accordingly, the measure of exposure to the trade shock is exactly the same as the measure in our reduced-form

Consistent with the empirical findings presented in Section 3, we find that workers from locations with higher exposure to the trade shock experience lower upward income mobility.

Figure 6: Impact of Trade Shock on Upward Income Mobility



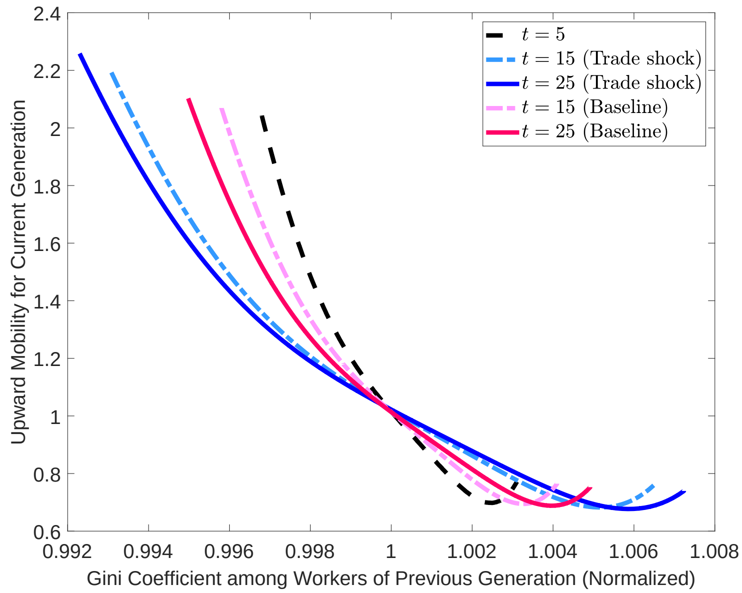
Note: Vertical axis shows upward income mobility for workers of the 11th, 15th, 20th and 25th generations relative to the 11th period (i.e., the period of the trade shock); horizontal axis shows the normalized measurement of exposure to the trade shock evaluated in each period. We show the fitted lines across 200 locations in the home country for each generation.

This highlights the channels of adjustment discussed in Section 4.5. In the home country, locations with large employment in manufacturing sector before the trade shock are more affected by the increase in productivity in the foreign country since decreased demand for labor in manufacturing in the home country leads to lower wages and land rent, in turn resulting in lower income. Yet, the persistence in workers' sectoral choices creates a friction in their intergenerational reallocation from manufacturing to services, which further depresses the manufacturing wage and, together with migration costs, slows down the pace of structural transformation. Given that the decline in income is sufficient to outweigh the gains from agglomeration economies over time, locations that retain workers in manufacturing have lower potential for upward income mobility. In particular, looking at the 15th generation in Figure 6, we find that agglomeration economies partially offset the impact of the trade shock. However, this offsetting effect is outweighed by the negative impact of trade shocks on labor mobility and workers in later periods.

Figure 7 illustrates the impact of the trade shock on the relationship between upward income mobility and income inequality and speaks to the Great Gatsby Curve depicted in Figure 5. For workers of the generation after the trade shock, the slope of the Great Gatsby Curve is flattened.

analysis, which is given in equation (2).

Figure 7: Impact of Trade Shock on Upward Income Mobility and Income Inequality



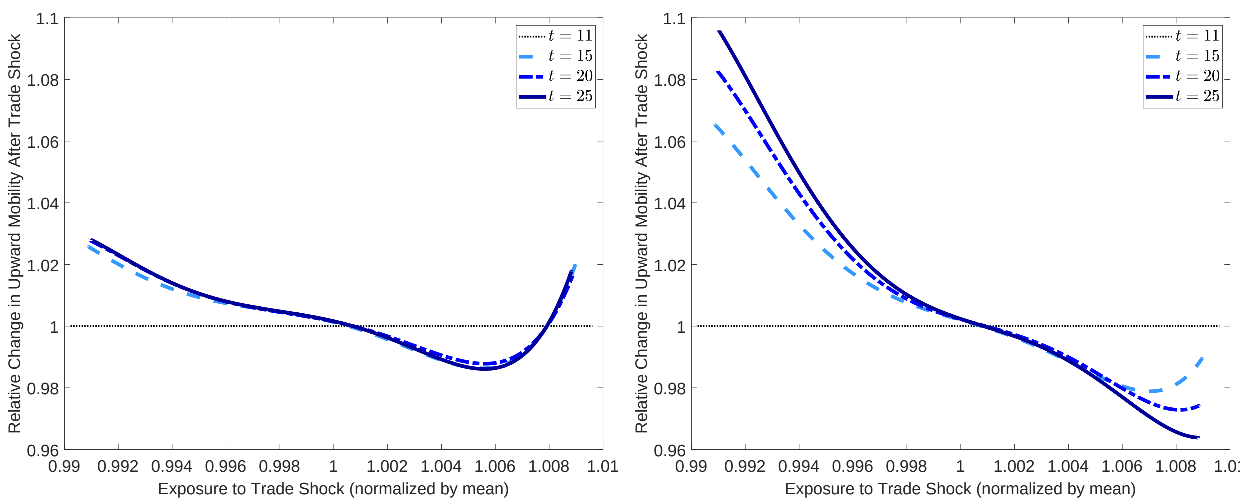
Note: Vertical axis shows upward income mobility for workers of the 5th, 10th and 25th generations; horizontal axis shows the normalized Gini coefficient among workers in each location for the 4th, 9th and 24th generations. We show the fitted lines across 200 locations in the home country for both the results of the baseline and the result of the trade shock in the 11th period.

This is consistent with the general equilibrium effect highlighted in the theory. First, income inequality as measured by the Gini coefficient shows more variation in the home country after the trade shock because the shock induces a further shift of workers from manufacturing to services in locations with less concentration of manufacturing, resulting in a narrow sectoral income gap. Second, workers from locations with a large share of employment in services gain upward income mobility after the trade shock because structural transformation together with the trade shock drives productivity growth in services through agglomeration economies, which allows workers to climb up the income ladder in the home country.

Lastly, we consider the different effects for workers who stay in the same location versus those who migrate to different locations within the home country. Figure 8 visualizes the relationship between upward income mobility and income inequality for different types of workers. Interestingly, in the left panel, we find that workers who remain in locations with the greatest trade exposure gain upward mobility. The intuition behind this finding is the following. While those locations are most exposed to the import shock, their comparative advantage in terms of fundamental productivity in manufacturing and their historical concentration of manufacturing workers sustain income growth over generations who stay there. At the same time, workers who move out of those locations are not able to achieve high upward income mobility as depicted in the right panel. The historical concentration of the manufacturing sector and the persistence in the sectoral choice of workers limit the gains from emigration since the trade shock decreases wage and employment opportunities in manufacturing also in other locations of the home country.

On the whole, more emigration from locations more exposed to the trade shock leads to an overall decline in upward income mobility. In a nutshell, the tension between two different forces is key to understand the cross-location variation in the impact of the trade shock on upward income mobility. As shown in the two panels, workers from locations with a relatively high employment share of manufacturing (i.e., a relatively high degree of trade exposure) suffer from both relatively small gains from productivity growth and limited opportunity for emigration. In contrast, workers from locations with the lowest degree of exposure to the trade shock gain more from the positive effects on both stayers and movers.

Figure 8: Decomposition of Impact of Trade Shock on Upward Income Mobility



(a) Workers Staying in the Same Location **(b)** Workers Migrating to the Different Location

Note: These figures show the decomposition of the relationship in Figure 6 into workers (a) who stay in the same location (Left panel) and (b) migrate to other locations in the home country (Right panel).

6 Educational Choices and Path Dependency

We have found that exposure to trade shocks at the commuting zone level leads to lower upward income mobility, conditional on initial inequality and other local characteristics. In our theoretical framework, this can be rationalized by: (i) the persistence of sector choices across generations in the commuting zone of origin, and (ii) geographical frictions that affect workers' mobility across space. However, while the baseline model succeeds in rationalizing the observed patterns in the data, it treats persistence as a black box. In this section we argue that an important mechanism hidden in the box is related to educational aspects that lead to persistent patterns of sectoral choice at the local level. We thus delve deeper into this mechanism, both theoretically and empirically.

6.1 *Empirical Evidence*

As a first step, in Table 8 we regress the standardized measure of absolute upward income mobility for workers from the 1980–1982 birth cohort in a commuting zone on a proxy for their enrollment in college. Specifically, we employ the share of enrolled first-time, first-year degree-seeking students over the total population of the commuting zone.[26] In each of the three columns we control for a different measure of initial income inequality, as in the baseline analysis. The estimated coefficients on college enrollment are always positive and significant, pointing to a positive association between college enrollment and upward income mobility at the commuting zone level.

As a second step, in Table 9 we show that commuting zones with higher employment shares in manufacturing prior to the China shock displayed lower college enrollment rates. Specifically, we regress the pre-sample (1988) share of enrolled first-time, first-year degree-seeking students over the total population in a commuting zone on the pre-sample share of manufacturing employment in the commuting zone, as employed in Table 4. In the first column of Table 9 we only control for initial income inequality. In the remaining columns, we show that the negative correlation between manufacturing share and college enrollment is robust to controlling for a wide range of socio-economic characteristics of the commuting zone, as employed in Table 6. This evidence is consistent with earlier results by Goldin and Katz (1997), who show that the higher education movement that swept the U.S. in the first four decades of the twentieth century was less prevalent in states with more manufacturing employment. Intuitively, because of the abundance of available employment opportunities in the manufacturing sector, residents of core industrial regions were more likely to regard college education as an unnecessary investment.

[26] We obtain data on college enrollment from the Integrated Postsecondary Education Data System (IPEDS), a system of surveys conducted annually by the U.S. Department of Education's National Center for Education Statistics (NCES). IPEDS annually collects comprehensive information from all institutions involved in federal student financial aid programs, covering institutional characteristics, student enrollments, graduation rates, and other metrics. To construct our measure of enrollment at the commuting zone level, we focus on first-time, first-year degree-seeking students to capture new enrollments as accurately as possible. Data is retrieved for each institution and then collapsed at the commuting zone level. Importantly, IPEDS data partially allows us to control for students' migration as the surveys provide information on the state of residence of students when first enrolled. Our baseline measure excludes students coming from a state different than the one where the university is located. Population data are from the U.S. Census Bureau. As a baseline we employ the share of enrolled first-time, first-year degree-seeking students over the total population in a commuting zone. We run robustness checks using age-specific population cohorts in the Online Appendix.

Table 8: Mobility and College Education

	(1)	(2)	(3)
Dependent variable:	Absolute Upward Mobility		
College enrollment in 1998	0.118^{a}	0.139^{a}	0.089^{a}
	(0.037)	(0.035)	(0.033)
Gini coefficient	-0.462^{a}		
	(0.084)		
Gini bottom 99%		-0.570^{a}	
		(0.075)	
Top 1% income share		-0.087^{b}	
		(0.038)	
% households in middle class			0.577^{a}
			(0.094)
Observations	591	591	591
R-squared	0.395	0.455	0.488
Estimation	OLS	OLS	OLS
Area FE	Yes	Yes	Yes

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. ^{a} and ^{b} indicate significance at the 1 and 5 percent levels, respectively.

Table 9: Manufacturing Share and College Enrollment Pre-Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Share of enrolled state-resident students over total commuting zone population in 1988								
Manufacturing employment share in 1990	-0.013^{a}	-0.013^{a}	-0.006^{c}	-0.012^{a}	-0.009^{a}	-0.012^{a}	-0.014^{a}	-0.013^{a}	-0.006^{c}
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Gini coefficient	0.001	0.001	0.002^{a}	0.001^{b}	0.001	0.001	0.001^{c}	0.000	0.002^{a}
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fraction of Black Population		Yes							Yes
Fraction with Commuting Time < 15min			Yes						Yes
Test Score Percentiles				Yes					Yes
High School Dropout Rate					Yes				Yes
Social Capital Index						Yes			Yes
Fraction of Children with Single Mother							Yes		Yes
Teenager Labor Force Participation Rate								Yes	Yes
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	580	580	580	579	481	580	580	580	480
R-squared	0.048	0.053	0.088	0.075	0.053	0.052	0.059	0.048	0.133

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Observations drop by 99 units (CZs) in columns (5) and (9) due to missing Dropout Rates. We lose one observation in column (4) and an additional one in (9) from missing Test Score Percentiles in one CZ. ^{a}, ^{b} and ^{c} indicate significance at the 1, 5, and 10 percent levels, respectively.

As a third and final step, in Table 10 we investigate the effect of trade exposure on college enrollment. The explanatory variable is the change in Chinese imports between 1991 and 2007, as in the baseline analysis. The dependent variable is the change in college enrollment around the same period. Specifically, we employ the change in shares of enrollment between 1988 and the average between 1998 and 2007 of first-year, first-time degree-seeking students in the commuting zone. As in Table 9, in the first column we only control for initial inequality, while in the remaining columns we include the whole battery of socio-demographic controls. The estimated coefficients on import exposure are negative and statistically significant across the board. This suggests that stronger exposure to import competition from China reduces enrollment in college education at the local level. In terms of magnitudes, the IV estimate in Column 9 suggests that a one standard deviation increase in exposure to Chinese imports leads to a decrease in college enrollment as a share of the total population by 0.15 percentage points, corresponding to 31% of the dependent variable's standard deviation. In Section D of the Online Appendix, we show that this result is robust to employing a number of alternative specifications, where we measure trade exposure over different time periods, and adopt several different ways of computing the college enrollment shares.

To summarize, through reduced-form analysis, we have shown that: (i) communing zones with higher levels of college enrollment exhibit higher levels of upward income mobility; (ii) commuting zones with higher manufacturing employment shares present lower college enrollment rates ex-ante; and (iii) commuting zones with higher exposure to trade shocks display a reduction in college enrollment over the sample period. Motivated by these findings, in the next subsection we extend the theoretical framework by including the educational choices of workers.

Table 10: Trade Exposure and College Enrollment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	**Shift in shares of enrollment between 1988 and 1998-2007**								
Exposure to Chinese imports '91-'07	-0.026^{c}	-0.028^{b}	-0.031^{b}	-0.029^{b}	-0.034^{b}	-0.029^{b}	-0.027^{b}	-0.031^{b}	-0.038^{a}
	(0.014)	(0.014)	(0.013)	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)
Gini coefficient	-0.041	-0.065^{c}	-0.070^{c}	-0.072^{b}	-0.062^{c}	-0.071^{b}	-0.074^{b}	-0.062^{c}	0.110^{b}
	(0.031)	(0.035)	(0.037)	(0.036)	(0.037)	(0.031)	(0.036)	(0.032)	(0.044)
Fraction of black population		Yes							Yes
Fraction with commuting time < 15min			Yes						Yes
Test score percentiles				Yes					Yes
High school dropout rate					Yes				Yes
Social capital index						Yes			Yes
Fraction of children with single mother							Yes		Yes
Teenager labor force participation rate								Yes	Yes
Estimation	IV	IV	IV	IV	IV	IV	IV	IV	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	575	575	575	574	476	575	575	575	475
First-stage results									
Kleibergen-Paap F-Statistic	16.68	16.48	15.12	16.44	69.99	16.28	16.74	16.23	67.30
Anderson-Rubin p-value	0.14	0.12	0.095	0.12	0.08	0.11	0.13	0.08	0.05

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Observations drop by 99 units (CZs) in columns (5) and (9) due to missing Dropout Rates. We lose one observation in column (4) and an additional one in (9) from missing Test Score Percentiles in one CZ. ^{a}, ^{b} and ^{c} indicate significance at the 1, 5, and 10 percent levels, respectively.

6.2 *Extended Model with Educational Choices*

We extend our baseline framework by adding workers' choices on education. Workers of generation t are born in period $t-1$ and work in period t, as in the baseline framework. They are homogeneous ex ante and are endowed with one unit of labor, which is inelastically provided in period t. Workers' decisions involve two steps. First, in the initial period $t-1$, they anticipate expected returns from education and work in different sectors, and determine whether to obtain higher education or not and which industry to work in. We let $e \in \{H, N\}$ refer to different types of education: higher education (H) and no higher education (N). Second, at the beginning of period t, workers draw amenity shocks and determine their location for work in period t. The educational choice is the additional element in this extended model, which is to be solved backward.

Solving the location choice In this extension, preferences are homothetic. The indirect utility of workers with education level e who move from their birthplace i to their workplace n depends on their consumption, migration costs (D_{nit}), the realization of the education wage premium in sectoral job $z^j_{it}(e)$, and idiosyncratic amenity shocks across locations (v_{nt}): $U^j_{nit}(e) = \frac{Y^j_{nt} v_{nt} z^j_{it}(e)}{D_{nit} P_{nt}}$. As in the baseline model, the individual idiosyncratic shocks (v_{nt}) follow a Fréchet distribution with shape parameter α. This implies that the expected utility for a worker in industry j and education level e with realization of the education premium $z^j_{it}(e)$ who moves from location i becomes:

$$\bar{U}^j_{it}(e) = \left(\lambda^j_{iit}\right)^{-1/\alpha} z^j_{it}(e), \tag{18}$$

where λ^j_{iit} is the share of workers who stay in their origin given their sector choice j. The education premium $z^j_{it}(e)$ is realized before the workplace choice is made. It thus depends on the birthplace, the sector, and the education decision, but not on the workplace. Hence, the workers' probabilities of mobility λ^j_{nit} can analogously be stated as in equation (10).

Solving the education and sector choice In the first period, workers independently draw their education premium $z^j_{it}(e)$ across different sectors and education levels. An idiosyncratic premium draw captures all the idiosyncratic factors that can cause an individual to get an extra benefit from getting sector-specific higher education in their origin. A worker's education premium $z^j_{it}(e)$ is independently drawn from the distribution:

$$\mathcal{F}^j_{it}(z \mid e) = \exp\left[-E_{it}(e)\mathcal{K}^j_{it}(e) z^{-\rho}\right], \tag{19}$$

where $\rho > 1$ is the Fréchet shape parameter that controls the dispersion of the education premium across workers and sectors; $E_{it}(e)$ captures quality of higher education in location i; and $\mathcal{K}^j_{it}(e)$ is the average premium for workers who choose sector j and education e in location i.

We normalize $E_{it}(N) = 1$ and assume that $E_{it}(H)$ reflects expenditures in higher education by the local government financed through a tax on land rents. In particular, we assume that the quality of higher education $E_{it}(H)$ is a function of total land rents Q_{it} with constant elasticity: $E_{it}(H) = Q_{it}^{\xi}$ where $\xi \in (0,1)$. This is equivalent to assuming a constant tax rate and a constant share of tax revenues spent on education.[27] These assumptions link the quality of local education to the economic performance of a location as land rents capitalize local amenity and productivity. Higher land revenue in the local economy allows for more public expenditures in education with ξ regulating the effect of such expenditures on the quality of education. Second, we assume that the average value of the education premium depends on past employment patterns in the location: $\mathcal{K}_{it}^{j}(e) = f_{\mathcal{K}}\left[\phi^{j}(e),\ L_{it-1}^{j}\right] = k^{\phi^{j}(e)L_{it-1}^{j}}$, where $\phi^{j}(e)$ is an education-specific shifter in the aggregate economy, and L_{it-1}^{j} is employment in sector j and location i when workers in generation t determine their sector and education. The parameter k is a constant greater than one that captures the degree of log-supermodularity of $\mathcal{K}_{it}^{j}(e)$. For any given exogenous increase in the education premium of the aggregate economy, its effects on the sector-location mean premium implied by distribution (19) are larger when there were more workers in the sector-location during the previous period: $\frac{\partial^2 \ln \mathcal{K}_{it}^{j}(e)}{\partial \phi^{j}(e) \partial L_{it-1}^{j}} = \ln k > 0$.

Workers choose education and sector to maximize (18) given the probability distribution (19). The share of workers who choose higher education and industry j given origin i evaluates to:

$$\chi_{it}^{j}(H) = \frac{\left(\lambda_{iit}^{j}\right)^{-\rho/\alpha} E_{it}(H)\mathcal{K}_{it}^{j}(H)}{\sum_{j'}\left(\lambda_{iit}^{j'}\right)^{-\rho/\alpha} E_{it}(H)\mathcal{K}_{it}^{j'}(H) + \sum_{j'}\left(\lambda_{iit}^{j'}\right)^{-\rho/\alpha}\mathcal{K}_{it}^{j'}(N)}, \tag{20}$$

which is higher when location i exhibits: (i) a higher standard of higher education $E_{it}(H)$, (ii) a larger average premium for higher education $\mathcal{K}_{it}^{j}(H)$, and (iii) a higher propensity for individuals to emigrate, resulting in a lower probability λ_{iit}^{j} of remaining in the location. Based on expression (20), the share of workers from origin i who choose higher education is:

$$\vartheta_{it}(H) = \sum_{j} \chi_{it}^{j}(H) \tag{21}$$

Accordingly, the share of workers who do not attain higher education equals $\vartheta_{it}(N) = 1 - \vartheta_{it}(H)$. Similar to the baseline model, there is persistence in sector choice in location i as a relatively large share of a sector's employment raises the associated average premium $\mathcal{K}_{it}^{j}(e)$, thereby increasing the likelihood of choosing that sector.

Lastly, we can also define the probability that individuals in location i choose sector j condi-

[27] The implications of trade shocks for public spending have been shown to be important for the response of a local economy (see Feler and Senses 2017).

tional on education e:

$$\varsigma_{it}^{j}(e) = \frac{\chi_{it}^{j}(e)}{\sum_{j'} \chi_{it}^{j'}(e)} = \frac{\mathcal{K}_{it}^{j}(e) \left(\lambda_{iit}^{j}\right)^{-\rho/\alpha}}{\sum_{j'} \mathcal{K}_{it}^{j'}(e) \left(\lambda_{iit}^{j'}\right)^{-\rho/\alpha}} \tag{22}$$

This concludes the characterization of the extended model.

6.3 *Implications derived from the Extended Model*

We can now derive two implications that are consistent with our empirical findings above.

Model implication #1: Higher education and sectoral composition First, we establish the link between workers' educational choices and the share of employment in the manufacturing sector at their origin. To achieve this, we consider the ratio of the probability of choosing higher education $\vartheta_{it}(H)$ to that of not doing that $\vartheta_{it}(N)$. We assume that $\phi^M(H) = \phi^M(N) = \phi^M$ holds. Then equation (21) implies:

$$\ln \frac{\vartheta_{it}(H)}{\vartheta_{it}(N)} = \xi \ln Q_{it} + \ln \left\{ \frac{1 + \left(\widetilde{\lambda}_{iit}\right)^{-\rho/\alpha} k^{[\phi^S(H)(1-\ell_i^M) - \phi^M \ell_i^M] L_{it-1}}}{1 + \left(\widetilde{\lambda}_{iit}\right)^{-\rho/\alpha} k^{[\phi^S(N)(1-\ell_i^M) - \phi^M \ell_i^M] L_{it-1}}} \right\}, \tag{23}$$

where $\widetilde{\lambda}_{iit} \equiv \lambda_{iit}^{S} / \lambda_{iit}^{M}$ is the share of workers who stay in their origin after choosing services relative to the share of those who stay there after choosing manufacturing, while $\ell_i^M \equiv L_{it-1}^M / L_{it-1}$ is the share of workers in the manufacturing sector in period $t-1$.

When $\phi^S(H) > \phi^S(N)$, the right-hand side of equation (23) decreases in the share of employment in the manufacturing sector (ℓ_i^M). Intuitively, the marginal return in education with respect to employment is the same for workers with and without higher education who are employed in the manufacturing sector, while it is different when when they are employed in different sectors. Consequently, in the absence of heterogeneity in migration patterns between different education levels within sector, workers are motivated to pursue higher education in locations where employment in the service sector is relatively large compared to the manufacturing sector. Under $\phi^S(H) > \phi^S(N)$, equation (22) implies:

$$\varsigma_{it}^{M}(N) > \varsigma_{it}^{M}(H) \tag{24}$$

When the marginal return from employment size in the services sector is substantial for workers with higher education, the probability of choosing jobs in the manufacturing sector conditional on not having higher education is greater than that for workers with higher education because individuals with higher education have an incentive to opt for employment opportunities in the services sector.

Model implication #2: Trade shock and higher education Next, we examine the impact of lower demand for locally produced output in the manufacturing sector due to the trade shock. This is larger in manufacturing-intensive locations. The change in the ratio of probabilities (23) is approximated as follows:

$$\ln \frac{\widehat{\vartheta}_{it}(H)}{\widehat{\vartheta}_{it}(N)} \approx \xi \ln \widehat{Q}_{it} + \left\{ \left(\frac{\widehat{\lambda}^{M}_{iit}}{\widehat{\lambda}^{S}_{iit}} \right)^{\rho/\alpha} - 1 \right\} \left[\varsigma^{M}_{it}(N) - \varsigma^{M}_{it}(H) \right], \tag{25}$$

where $\varsigma^{M}_{it}(N)$ and $\varsigma^{M}_{it}(H)$ are ranked as in (24).[28]

There are two ways in which import penetration leads to lower educational attainment in manufacturing-intensive locations. First, the import penetration results in decreased tax revenues for the local economy ($\ln \widehat{Q}_{it} < 0$), which in turn lowers the quality of higher education. This is captured by the first term on the right-hand side of equation (25). Second, given the ex-ante differences in sector choices between workers' education types ($\varsigma^{M}_{it}(N) > \varsigma^{M}_{it}(H)$), changes in the local probabilities of non-migration have an impact on the proportion of individuals who opt for higher education. As a result of decreased demand for local manufacturing output, which depresses local wages, in manufacturing-intensive locations the trade shock induces a larger fraction of workers to emigrate among those who have chosen manufacturing than among those who have chosen services. Accordingly, we have $\widehat{\lambda}^{M}_{iit} < \widehat{\lambda}^{S}_{iit}$ and the second term on the right-hand side of equation (25) is negative. As a result, the trade shock reduces the likelihood of higher education attainment in locations with a greater ex-ante share of employment in the manufacturing sector.

7 Conclusion

This paper examines the relationship between globalization and intergenerational income mobility. In the empirical analysis, we show that U.S. commuting zones that are more exposed to trade display lower upward income mobility down the line. In particular, rising exposure to Chinese import competition between 1991 and 2007 in the region of origin lowers the mobility of the cohort of U.S. workers born in 1980–1982, as evaluated based on their income in 2011–2012, when they are in their early 30s. This evidence is robust to controlling for the initial inequality in parents' income and a proxy for historical social mobility in the area, along with a large number of other commuting zone characteristics. It is also robust to considering import competition from different foreign countries.

As for potential channels through which trade exposure may decrease intergenerational income mobility, we have reported evidence consistent with higher exposure to Chinese import

[28]See Section E of the Online Appendix for derivation.

competition reducing educational attainment. First, communing zones with higher levels of college enrollment exhibit higher levels of upward income mobility. Second, commuting zones with higher manufacturing employment shares present lower college enrollment rates ex-ante. Third, commuting zones with higher exposure to trade shocks display a reduction in college enrollment over the sample period.

To rationalize these empirical findings, we have presented a general equilibrium model with overlapping generations that features differential rates of structural transformation across locations in a country. Barriers for workers to switch locations due to migration costs, and to switch sectors due to their historical exposure to agglomeration in the birthplace, lead to low intergenerational income mobility for workers in locations with industries highly exposed to a trade shock. The numerical solutions of the model for the two-sector and two-country framework show an equilibrium pattern consistent with our empirical findings. When the model is extended to allow for an endogenous educational choice, it also describes how the education channel may actually work.

This paper shows that international trade is a significant driver of divergence in social mobility across different areas of the U.S., allowing one to understand why some regions have been left behind in terms of mobility as the world moved forward with globalization. Our work highlights an additional, dynamic dimension of the distributional consequences of trade, that has been understudied so far. Besides raising inequality across industries and regions for current workers, trade exposure seems to reduce social mobility opportunities for the next generation. This may enhance discontent towards trade and nourish the globalization backlash in public opinion and electoral dynamics.

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Online Appendix for "Trade and Intergenerational Income Mobility: Theory and Evidence from the U.S." (Not for publication)

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Introduction Section A presents additional robustness checks on the empirical analysis of Section 3. Section B presents the derivation of some results of Section 4 in the main text. Section C contains supplementary results for numerical solutions discussed in Section 5. Section D includes results of robustness checks on the empirical analysis of Section 6. Section E contains some derivations for the theory part of Section 6.

A Additional Reduced-form Results for Section 3

Table A.1: Relative Income Mobility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Relative income mobility							
Exposure to Chinese imports '91-'07	0.018	0.067^a	0.019	0.069^a	0.021	0.075^a	0.020	0.064^b
	(0.013)	(0.025)	(0.013)	(0.025)	(0.013)	(0.023)	(0.012)	(0.026)
Gini coefficient			0.212^a	0.217^a				
			(0.076)	(0.077)				
Gini bottom 99%					0.411^a	0.421^a		
					(0.082)	(0.082)		
Top 1% income share					−0.023	−0.023		
					(0.033)	(0.035)		
% households in middle class							-0.390^a	-0.397^a
							(0.107)	(0.104)
Estimation	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	693	693	693	693	693	693	693	693
R-squared	0.32	-	0.35	-	0.40	-	0.41	-
First-Stage Results								
Exports to other high income countries	-	0.938^a	-	0.938^a	-	0.938^a	-	0.940^a
	-	(0.154)	-	(0.154)	-	(0.155)	-	(0.152)
Kleibergen-Paap F-Statistic	-	37.33	-	37.26	-	36.65	-	38.17
Anderson-Rubin p-value	-	0.0162	-	0.0117	-	< 0.01	-	0.0275

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Columns (1), (3), (5) and (7) report OLS estimates; Columns (2), (4),(6) and (8) report IV estimates. ^{a} indicates significance at the 1 percent level.

Table A.2: Including Fixed Effects for U.S. Census Divisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Absolute upward income mobility							
Exposure to Chinese imports '91-'07	-0.010	-0.045[b]	-0.014	-0.058[a]	-0.017[c]	-0.066[a]	-0.016[c]	-0.049[a]
	(0.009)	(0.020)	(0.010)	(0.019)	(0.010)	(0.017)	(0.009)	(0.018)
Gini coefficient			-0.381[a]	-0.393[a]				
			(0.067)	(0.066)				
Gini bottom 99%					-0.532[a]	-0.550[a]		
					(0.064)	(0.062)		
Top 1% income share					-0.083[a]	-0.088[a]		
					(0.030)	(0.029)		
% households in middle class							0.529[a]	0.539[a]
							(0.085)	(0.084)
Estimation	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Division Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	693	693	693	693	693	693	693	693
R-squared	0.49	-	0.58	-	0.63	-	0.65	-
First-Stage Results								
Exports to other high income countries	-	0.908[a]	-	0.907[a]	-	0.907[a]	-	0.907[a]
	-	(0.159)	-	(0.159)	-	(0.161)	-	(0.158)
Kleibergen-Paap F-Statistic	-	32.81	-	32.55	-	31.90	-	33.05
Anderson-Rubin p-value	-	0.0315	-	< 0.01	-	< 0.01	-	0.0160

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census division dummies; standard errors are clustered at the state level. Columns (1), (3), (5) and (7) report OLS estimates; Columns (2), (4),(6) and (8) report IV estimates. [a] and [b] indicate significance at the 1 and 5 percent levels, respectively.

B Theoretical Appendix for Section 4

Derivation of expenditure share (9) The underlying utility maximization for a worker in location n and sector j' is:

$$\begin{aligned} &\{q_{j|nj't}(\omega)\}_j \in \arg\max_{\{c_j\}} \; Q^{j'}_{nt}(\omega) \\ &\text{s.t.} \quad \sum_j p^j_{nt} q_j \leq Y^{j'}_{nt}, \quad \sum_j q_j^{(\sigma-1)/\sigma} Q^{j'}_{nt}(\omega)^{(\theta_j-\sigma)/\sigma} = 1, \end{aligned} \tag{B.1}$$

where $\sigma < 1$ and $\theta_j \geq 1$. The first constraint is a budget constraint, and the second constraint defines the aggregate consumption index $Q^{j'}_{nt}$ implicitly. When $\theta_j = 1$ for all j, this is reduced to standard homothetic CES demand system.

Solving this, the corresponding price index is defined as an implicit solution to:

$$P^{j'}_{nt} = \left[\sum_j \left(p^j_{nt}\right)^{1-\sigma} \left(P^{j'}_{nt}\right)^{1-\theta_j} \left(Y^{j'}_{nt}\right)^{\theta_j-1}\right]^{1/(1-\sigma)} \tag{B.2}$$

Using the price index, the expenditure share on sector j by workers in sector j' is:

$$\mu_{j|nj't} = \left(p^j_{nt}/P^{j'}_{nt}\right)^{1-\sigma} \left(Y^{j'}_{nt}/P^{j'}_{nt}\right)^{\theta_j-1} \tag{B.3}$$

Therefore, non-homotheticity materializes as long as $\theta_j \neq 1$, in which case θ_j captures the difference in the slope of the Engel curve across sectors.

Derivation of (11) Individuals of generation t receive taste shocks for each industry and the number of shocks m^j_{it} follows Poisson distribution:

$$\mathcal{F}^j_{it}(m) \equiv \mathbf{Pr}(m^j_{it} = m) = \frac{(\mathcal{B}^j_{it-1})^m e^{-\mathcal{B}^j_{it-1}}}{m!}, \tag{B.4}$$

where $\mathcal{B}^j_{it-1} = \left(L^j_{it-1}\right)^{\psi}$. The value of each shock is supposed to be following the Pareto distribution for every sector: $1 - \left(z/z_{\min}\right)^{-\eta}$ with $\eta > 1$. The important assumption in our setting is that the number of arrival shocks is specific to pair of industry and location, while the size of shocks is independent to industry and location.

An individual picks up the largest value from tastes. Its c.d.f. is:

$$\begin{aligned}
\mathbf{Pr}\left(z^j_{it} \leq z\right) &= \sum_{m=1}^{\infty} \left(\prod_{m'=1}^{m} \mathbf{Pr}\left(z^j_{it}(m') \leq z\right) \right) \mathcal{F}^j_{it}(m) + \mathcal{F}^j_{it}(0) \\
&= \sum_{m=0}^{\infty} \left(1 - (z/z_{\min})^{-\eta}\right)^m \frac{(\mathcal{B}^j_{it-1})^m e^{-\mathcal{B}^j_{it-1}}}{m!} \\
&= \exp\left[-\mathcal{B}^j_{it-1} \left(\frac{z}{z_{\min}} \right)^{-\eta} \right]
\end{aligned} \tag{B.5}$$

Then, we define the c.d.f. of indirect utility:

$$G^j_{it}(u) = \mathbf{Pr}\left(\bar{U}^j_{it} z^j_{it} \leq u\right) = \exp\left[-\mathbb{V}^j_{it} u^{-\eta}\right] \tag{B.6}$$

where $\mathbb{V}^j_{it} \equiv \mathcal{B}^j_{it-1}\left(z_{\min}\bar{U}^j_{it}\right)^{\eta}$. With this distribution, we derive the pattern of choosing industry j among cohort t in location i:

$$\begin{aligned}
\kappa^j_{it} &= \mathbf{Pr}\left(\bar{U}^j_{it} z^j_{it} \geq \bar{U}^{j'}_{it} z^{j'}_{it},\ \forall\, j' \neq j\right) \\
&= \int_{\underline{u}}^{\infty} g^j_{it}(u) \prod_{j' \neq j} G^{j'}_{it}(u) du \\
&= \frac{\mathbb{V}^j_{it}}{\sum_{j'} \mathbb{V}^{j'}_{it}} \left[e^{-\sum_j \mathbb{V}^j_{it} u^{-\eta}} \right]_{\underline{u}}^{\infty} \\
&\to \frac{\mathcal{B}^j_{it-1}\left(\bar{U}^j_{it}\right)^{\eta}}{\sum_{j'} \mathcal{B}^{j'}_{it-1}\left(\bar{U}^{j'}_{it}\right)^{\eta}} \quad (as\ z_{\min} \to 0)
\end{aligned} \tag{B.7}$$

In the last part of the equation, we take the minimum of Pareto distribution (i.e., lower bound of the Pareto distribution) to zero and expand its support to $(0, \infty)$.

In addition, the distribution of indirect utility satisfies:

$$\begin{aligned} 1 - G_{it}(u) &= 1 - \prod_j \exp\left[-\mathbb{V}_{it}^j u^{-\eta}\right] \\ &= 1 - \exp\left(-\Xi_{it} u^{-\eta}\right), \end{aligned} \tag{B.8}$$

where $\Xi_{it} = \sum_j \mathbb{V}_{it}^j$. Thus, the average of indirect utility for the generation t born in i can be expressed as:

$$\int_{\underline{u}}^{\infty} u dG_{it}(u) = \int_0^{\Xi_{it}\underline{u}^{-\eta}} (y/\Xi_{it})^{-1/\eta} \exp(-y) dy \to \Xi_{it}^{1/\eta} \tag{B.9}$$

When we substitute this into (B.7), we obtain (11) in the main text.

Labor market clearing condition (12) Given probabilities (10) and (11), the mass of workers who decide to work in sector j and location n is a summation of such workers across their origins, including all locations in the home and foreign:

$$\sum_i \lambda_{nit}^j \kappa_{it}^j L_{it-1}, \tag{B.10}$$

where the total population of generation t from location i is equal to the mass of workers of the previous generation in the location (L_{it-1}). This defines the labor supply.

Total income of workers in location i is $Y_{it}^j L_{it}^j$ and, using (9) their expenditure on sector j is given by: $x_{it}^j = \sum_{j'} \mu_{j|ij't} Y_{it}^{j'} L_{it}^{j'}$. Zero profit condition and trade probabilities (6) implies that total export of location n in sector j is:

$$X_{nt}^j = \sum_i \pi_{int}^j x_{it}^j \tag{B.11}$$

Under the Cobb-Douglas production function, the total labor demand in location n and sector j is:

$$\frac{\beta_j}{w_{nt}^j} X_{nt}^j \tag{B.12}$$

Combining them yields the labor market clearing condition (12) in the main text.

General equilibrium Conditional on the employment distribution in period $t-1$, $\{L_{it-1}^j\}$, we show how the equilibrium is determined in period t. To simplify the notation, we let $\epsilon_j = \epsilon$ and $\beta_j = \beta$ for all j without loss of generality. The expected utility conditional on job choice j for a worker born in location i and real income $\{W_{nt}^j\}$ satisfies:

$$\bar{U}_{it}^j = \left[\sum_n \left(W_{nt}^j / D_{nit}\right)^{\alpha}\right]^{1/\alpha} \tag{B.13}$$

There is a unique mapping between real income and average utility, and the mapping is increasing and homogeneous of degree one. The labor movement implies:

$$L_{nt}^{j}=\sum_{i}\frac{D_{nit}^{-\alpha}\left(W_{nt}^{j}\right)^{\alpha}}{\sum_{l}D_{lit}^{-\alpha}\left(W_{lt}^{j}\right)^{\alpha}}\frac{\mathcal{B}_{it-1}^{j}\left[\sum_{n}\left(W_{nt}^{j}/D_{nit}\right)^{\alpha}\right]^{\eta/\alpha}}{\sum_{j'}\mathcal{B}_{it-1}^{j'}\left[\sum_{n}\left(W_{nt}^{j'}/D_{nit}\right)^{\alpha}\right]^{\eta/\alpha}}L_{it-1} \tag{B.14}$$

Employment distribution is uniquely determined by the real income, and the mapping is increasing and homogeneous of degree zero in real income. Turning to prices, the price of the final good in location n and sector j is uniquely determined given wage ($\boldsymbol{w}$) and employment distribution ($\boldsymbol{L}$) such that:

$$\left(p_{nt}^{j}\right)^{-\epsilon}=\bar{\gamma}^{-\epsilon}\left[\sum_{i}\left(\tau_{int}^{j}\right)^{-\epsilon}\left(\frac{\left(w_{it}^{j}\right)^{\beta}\left(r_{it}\right)^{1-\beta}}{a_{it}^{j}}\right)^{-\epsilon}\left(L_{it}^{j}\right)^{\gamma\epsilon}\right] \tag{B.15}$$

where $\bar{\gamma}$ is constant. Note that land rent is determined by

$$r_{nt}T_{n}=\frac{1-\beta}{\beta}\sum_{j}w_{nt}^{j}L_{nt}^{j} \tag{B.16}$$

and the income of workers in location n and sector j is:

$$Y_{nt}^{j}=w_{nt}^{j}+\frac{r_{nt}T_{n}}{L_{nt}}=w_{nt}^{j}+\frac{1-\beta}{\beta}\sum_{j}\frac{w_{nt}^{j}L_{nt}^{j}}{L_{nt}} \tag{B.17}$$

Combining them together, the real income is a solution to

$$\left(\frac{w_{nt}^{j}+\frac{1-\beta}{\beta}\sum_{j}\frac{w_{nt}^{j}L_{nt}^{j}}{L_{nt}}}{W_{nt}^{j}}\right)^{1-\sigma}=\bar{\gamma}^{1-\sigma}\sum_{j}\left(p_{nt}^{j}\right)^{1-\sigma}\left(W_{nt}^{j'}\right)^{\theta_{j}-1} \tag{B.18}$$

As $\sigma-1<0$ and $\theta_{j}-1>0$, real income W_{nt}^{j} is uniquely determined given ($\boldsymbol{w}$, $\boldsymbol{L}$). Next, we consider labor demand. Total expenditure on sector j in location i is given by:

$$x_{it}^{j}=\sum_{j'}\left(\frac{p_{it}^{j}}{P_{it}^{j'}}\right)^{1-\sigma}\left(W_{it}^{j'}\right)^{\theta_{j}-1}Y_{it}^{j'}L_{it}^{j'} \tag{B.19}$$

Total export of location n in sector j is:

$$X_{nt}^{j}=\sum_{i}\frac{\left(\tau_{int}^{j}c_{it}^{j}\right)^{-\epsilon}}{\sum_{l}\left(\tau_{lnt}^{j}c_{lt}^{j}\right)^{-\epsilon}}\left[\sum_{j'}\left(\frac{p_{it}^{j}}{P_{it}^{j'}}\right)^{1-\sigma}\left(W_{it}^{j'}\right)^{\theta_{j}-1}Y_{it}^{j'}L_{it}^{j'}\right] \tag{B.20}$$

Therefore, the labor market clearing condition implies:

$$w_{nt}^{j} = \frac{\beta_j}{L_{nt}^{j}} \left\{ \sum_i \frac{\left[\tau_{int}^{j} \left(\frac{\left(w_{it}^{j}\right)^{\beta} \left(r_{it}\right)^{1-\beta}}{a_{it}^{j} \left(L_{it}^{j}\right)^{\gamma_j}} \right)\right]^{-\epsilon}}{\sum_l \left[\tau_{lnt}^{j} \left(\frac{\left(w_{lt}^{j}\right)^{\beta} \left(r_{lt}\right)^{1-\beta}}{a_{lt}^{j} \left(L_{lt}^{j}\right)^{\gamma_j}} \right)\right]^{-\epsilon}} \left[\sum_{j'} \left(\frac{p_{it}^{j}}{P_{it}^{j'}} \right)^{1-\sigma} \left(W_{it}^{j'}\right)^{\theta_j - 1} Y_{it}^{j'} L_{it}^{j'} \right] \right\} \tag{B.21}$$

The equilibrium in period t is fully characterized by $(\boldsymbol{L}, \boldsymbol{W}, \boldsymbol{w})$ that solve equations: labor mobility (B.14); utility maximization (B.18); and labor market clearing condition (B.21). By construction, the system of equations takes the form of fixed point equations. Then, for positive wages and employment, we can constitute a convex subset for real income, and (B.18) provides the existence of such positive and finite real income. By using the same augment, we can define the convex subset for wages and employment such that we can characterize the positive and finite equilibrium variables. This proves the existence of equilibrium.

Derivation of equation (17) We use the notation $\widehat{X}$ for endogenous variable X to refer to the variable after the trade shock in period $t-1$, $\widetilde{X}$ relative to the baseline X. We also define:

$$\begin{aligned} \bar{\mathcal{R}}_{it-1} &\equiv \mathbb{E}[\mathcal{R}_{it-1}^{j}(\omega)], \\ \mathcal{R}_{it}^{*} &\equiv \mathbb{E}[\mathcal{R}_{nt}^{j}(\omega)|\boldsymbol{\kappa}, \boldsymbol{\lambda}] \end{aligned} \tag{B.22}$$

in the definition (16). $\bar{\mathcal{R}}_{it-1}$ is the average income percentile of workers of generation $t-1$ in location i, and $\mathcal{R}_{it}^{*}$ is the average income percentile of workers of generation t whose origin is location i. Given the shock in period $t-1$, the change in intergenerational income measure in the model is given by:

$$\widehat{\Omega}_{it} = \frac{\widehat{\mathcal{R}}_{it}^{*}}{\widehat{\bar{\mathcal{R}}}_{it-1}} \tag{B.23}$$

In this expression, the denominator is the change in the average income rank of workers of generation $t-1$ in location i, and this is given by:

$$\begin{aligned} \widehat{\bar{\mathcal{R}}}_{it-1} &= \frac{\sum_j f_{it-1}^{j} \widetilde{\mathcal{R}}_{it-1}^{j}}{\sum_j f_{it-1}^{j} \mathcal{R}_{it-1}^{j}} \\ &= \sum_j \underbrace{\frac{f_{it-1}^{j} \mathcal{R}_{it-1}^{j}}{\sum_{j'} f_{it-1}^{j'} \mathcal{R}_{it-1}^{j'}}}_{=\Theta_{ijt-1}^{\mathbb{F}}} \frac{\widetilde{\mathcal{R}}_{it-1}^{j}}{\mathcal{R}_{it-1}^{j}} \\ &= \sum_j \Theta_{ijt-1}^{\mathbb{F}} \widehat{\mathcal{R}}_{it-1}^{j} \end{aligned} \tag{B.24}$$

where the income rank of workers is changed by $\widehat{\mathcal{R}}^j_{it-1} = \widetilde{\mathcal{R}}^j_{it-1}/\mathcal{R}_{ijt-1}$ after the shock. We note that the distribution of workers across sectors in location i for generation $t-1$, f^j_{it-1}, is not affected by the shock, as the shock is not predicted before. Next, the numerator of equation (B.23) is the average income rank of generation t from location i after the shock relative to the baseline. Then, we can derive:

$$\begin{aligned}
\widehat{\mathcal{R}}^*_{it} &= \sum_j \underbrace{\frac{\kappa^j_{it} s^j_{it}}{\sum_{j'} \kappa^{j'}_{it} s^{j'}_{it}}}_{=\Theta^{\mathbb{K}}_{ijt}} \widehat{\kappa}^j_{it} \widehat{s}^j_{it} \\
&= \sum_j \Theta^{\mathbb{K}}_{ijt} \widehat{\kappa}^j_{it} \widehat{s}^j_{it},
\end{aligned} \tag{B.25}$$

where $s^j_{it} \equiv \sum_n \lambda^j_{nit} \mathcal{R}^j_{nt}$. In turn, the change in sector choice probabilities (B.7) is given by:

$$\widehat{\kappa}^j_{it} = \frac{(\widehat{\bar{U}}^j_{it})^\eta}{\sum_{j'} \kappa^{j'}_{it} (\widehat{\bar{U}}^{j'}_{it})^\eta} \tag{B.26}$$

Using the migration probabilities, we can express the change in average utility of workers from location i and in sector j:

$$\bar{U}^j_{it} = \left(\lambda^j_{iit}\right)^{-1/\alpha} W^j_{it} \tag{B.27}$$

When we substitute (B.27) into (B.26), we obtain:

$$\widehat{\kappa}^j_{it} = \frac{\left(\widehat{\lambda}^j_{iit}\right)^{-\eta/\alpha} \left(\widehat{W}^j_{it}\right)^\eta}{\sum_{j'} \kappa^{j'}_{it} \left(\widehat{\lambda}^{j'}_{iit}\right)^{-\eta/\alpha} \left(\widehat{W}^{j'}_{it}\right)^\eta} \tag{B.28}$$

Next, we also consider the change in migration patterns through the change in s^j_{it}. By definition of the migration probabilities (10), we can rewrite the term s^j_{it} by:

$$\begin{aligned}
s^j_{it} &= \sum_n \lambda^j_{nit} \mathcal{R}^j_{nt} \\
&= \lambda^j_{iit} \sum_n \frac{W^j_{nt}}{W^j_{it}} \frac{\mathcal{R}^j_{nt}}{D_{nit}}
\end{aligned} \tag{B.29}$$

Then, its change after the shock in period $t-1$ becomes:

$$\begin{aligned}
\widehat{s}^j_{it} &= \widehat{\lambda}^j_{iit} \sum_n \underbrace{\frac{\lambda^j_{nit} \mathcal{R}^j_{nt}}{\sum_{n'} \lambda^j_{n'it} \mathcal{R}^j_{n't}}}_{=\Theta^{\mathbb{M}}_{nijt}} \frac{\widehat{W}^j_{nt}}{\widehat{W}^j_{it}} \widehat{\mathcal{R}}^j_{nt} \\
&= \widehat{\lambda}^j_{iit} \sum_n \Theta^{\mathbb{M}}_{nijt} \frac{\widehat{W}^j_{nt}}{\widehat{W}^j_{it}} \widehat{\mathcal{R}}^j_{nt}
\end{aligned} \tag{B.30}$$

Lastly, plugging (B.24), (B.25), (B.28) and (B.30) into (B.23) leads to the equation (17) in the main text.

C Additional Figures for Section 5

The change in sectoral employment share in the home country is illustrated in Figure C.1. The home country experiences a structural transformation from manufacturing to services in terms of employment share, regardless of the trade shock. This is a result of exogenous productivity growth and non-homothetic preferences, which means that expenditure is shifting from manufacturing to services. Following the trade shock in the 11th period, structural transformation is accelerated because of the productivity growth in the foreign country. In Figure C.2, we show the employment share of the manufacturing sector in period 10 on the horizontal axis and the change in manufacturing employment share between the 10th and 20th periods. This confirms the heterogeneous effects of the trade shock on local labor markets. After the trade shock, locations with higher employment shares experience a relative decline in manufacturing employment share (i.e., a higher rate of structural transformation).

Figure C.1: Sectoral Employment in the Home Country

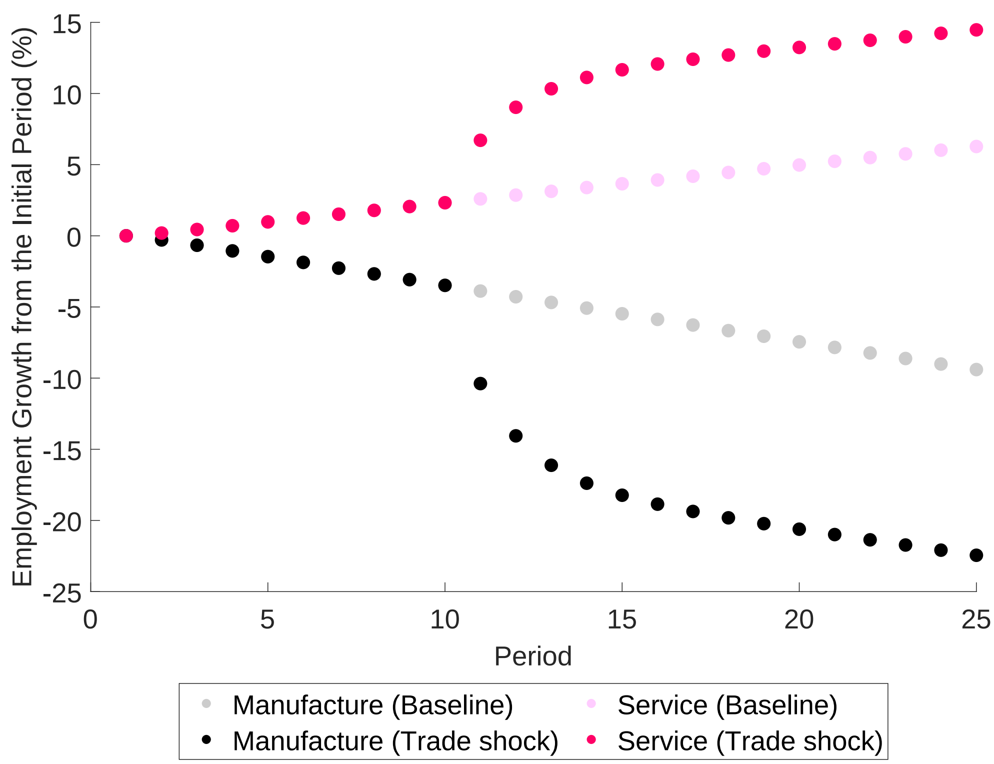
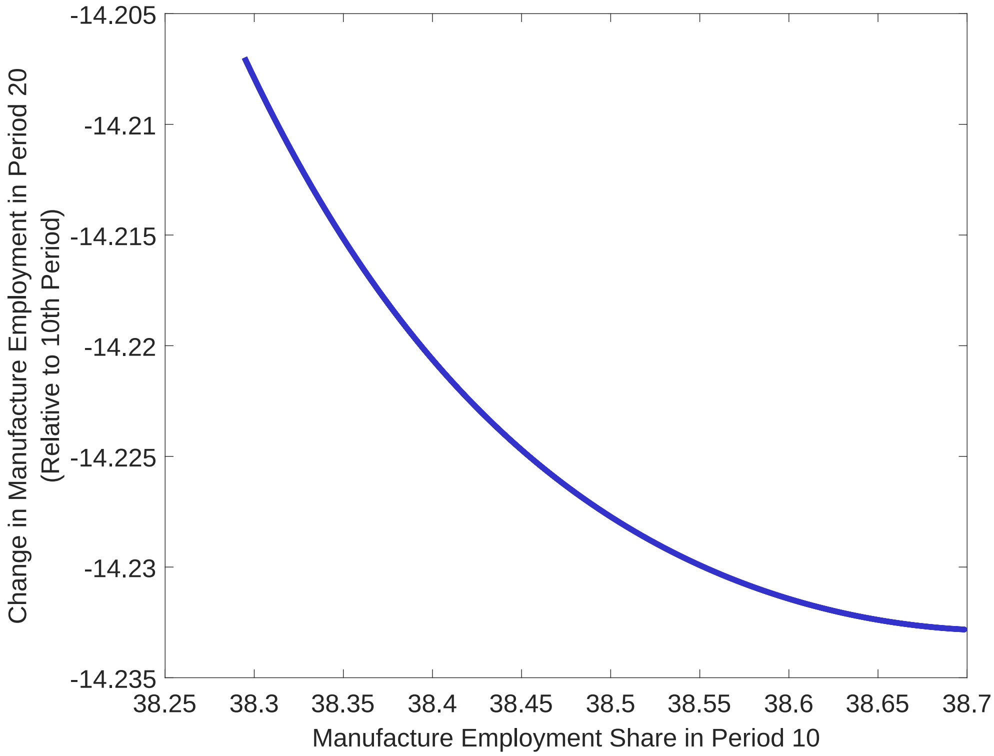


Figure C.2: Change in Sectoral Employment in the Home Country



D Additional Reduced-form Results for Section 6

Table D.1 presents the results of robustness tests for the analysis in Table 10 of Section 6. The set of controls is the same as in Column (9) of Table 10 across all columns. In Column (1), we restrict the denominator of college enrollment shares by considering the population in the 15-29 age cohort instead of the total population of the commuting zone. In Column (2), we compute exposure to Chinese imports in the sub-period 1991–1995, and consider the enrollment in 1998 as a post-shock measure. In Columns (3) to (5), we include students from other states in the numerator of the college enrollment share; in this case, thanks to better data availability, we consider the average enrollment share between 1988 and 1990 rather than just 1988, as a pre-sample measure. The estimated coefficients on import exposure are negative and significant across the board, and very similar in magnitude compared to the baseline analysis.

Table D.1: Trade Exposure and College Enrollment - Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Shift in shares of enrollment				
Exposure to Chinese imports '91-'07	-0.156^a		-0.020^a	-0.071^a	
	(0.073)		(0.005)	(0.022)	
Exposure to Chinese imports '91-'95		-0.136^a			-0.107^b
		(0.062)			(0.044)
Gini coefficient	-0.382^b	-0.085^b	-0.041^b	-0.140	-0.039
	(0.180)	(0.043)	(0.020)	(0.089)	(0.030)
Fraction of Black Population	Yes	Yes	Yes	Yes	Yes
Fraction with Commuting Time < 15min	Yes	Yes	Yes	Yes	Yes
Test Score Percentiles	Yes	Yes	Yes	Yes	Yes
High School Dropout Rate	Yes	Yes	Yes	Yes	Yes
Social Capital Index	Yes	Yes	Yes	Yes	Yes
Fraction of Children with Single Mother	Yes	Yes	Yes	Yes	Yes
Teenager Labor Force Participation Rate	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
15-29 Age Cohort	Yes	-	-	Yes	-
Non State-Resident Students	-	-	Yes	Yes	Yes
Observations	475	473	488	488	486
First-stage results					
Kleibergen-Paap F-Statistic	67.30	21.64	69.00	69.00	19.46
Anderson-Rubin p-value	0.09	0.02	<0.01	<0.01	0.04

Note: Cross-section of U.S. commuting zones; all columns include U.S. Census region dummies; standard errors are clustered at the state level. Column (1) considers the 15-29 age cohort to calculate the share of enrollment; Column (2) shows results for import competition from China over 1991-95 and considers enrollment in 1998 as a post-shock measure. From column (3) to (5) non state-resident students are included in the analysis; Column (3) considers the total population at the CZ-level as the denominator; Column (4) considers the 15-29 age cohort as the denominator; Column (5) shows results for import competition from China over 1991-95 and considers the average enrollment between 1997 and 1999 as a post-shock measure. ^{a} and ^{b} indicate significance at the 1 and 5 percent levels, respectively.

E Theoretical Appendix for Section 6

Derivation of Model Implication (25) When parameters satisfy $\phi^M(H) = \phi^M(N)$, we have $\mathcal{K}^M_{it}(H) = \mathcal{K}^M_{it}(N)$. We let

$$\begin{aligned} \omega^1_{it} &= (\widetilde{\lambda}_{iit})^{-\rho/\alpha} k^{[\phi^S(H)(1-\ell^M_i)-\phi^M \ell^M_i]L_{it-1}} \\ &= (\widetilde{\lambda}_{iit})^{-\rho/\alpha} \frac{\mathcal{K}^S_{it}(H)}{\mathcal{K}^M_{it}}, \end{aligned}$$

and

$$\begin{aligned} \omega^2_{it} &= (\widetilde{\lambda}_{iit})^{-\rho/\alpha} k^{[\phi^S(N)(1-\ell^M_i)-\phi^M \ell^M_i]L_{it-1}} \\ &= (\widetilde{\lambda}_{iit})^{-\rho/\alpha} \frac{\mathcal{K}^S_{it}(N)}{\mathcal{K}^M_{it}} \end{aligned}$$

Then, (23) can be written as:

$$\ln \frac{\vartheta_{it}(H)}{\vartheta_{it}(N)} = \xi \ln Q_{it} + \ln \frac{1+\omega^1_{it}}{1+\omega^2_{it}}$$

For changes in fundamentals in period t, we denote x' the equilibrium variable after the change. Then, we can write the difference between the new equilibrium and the original equilibrium:

$$\ln \frac{\vartheta_{it}(H)'}{\vartheta_{it}(N)'} - \ln \frac{\vartheta_{it}(H)}{\vartheta_{it}(N)} = \xi \ln \frac{Q_{it}'}{Q_{it}} + \ln \frac{1+\omega^{1\prime}_{it}}{1+\omega^1_{it}} - \ln \frac{1+\omega^{2\prime}_{it}}{1+\omega^2_{it}} \tag{E.1}$$

The right-hand side of this is approximated by:

$$\ln \frac{\vartheta_{it}(H)'}{\vartheta_{it}(N)'} - \ln \frac{\vartheta_{it}(H)}{\vartheta_{it}(N)} = \xi \ln \frac{Q_{it}'}{Q_{it}} + \frac{\omega^{1\prime}_{it} - \omega^1_{it}}{1+\omega^1_{it}} - \frac{\omega^{2\prime}_{it} - \omega^2_{it}}{1+\omega^2_{it}} \tag{E.2}$$

Therefore, using the notation $\widehat{x} = x'/x$,

$$\ln \frac{\widehat{\vartheta}_{it}(H)}{\widehat{\vartheta}_{it}(N)} = \xi \ln \widehat{Q}_{it} + \frac{\omega^{1\prime}_{it} - \omega^1_{it}}{1+\omega^1_{it}} - \frac{\omega^{2\prime}_{it} - \omega^2_{it}}{1+\omega^2_{it}} \tag{E.3}$$

By definition,

$$\begin{aligned} \omega^{1\prime}_{it} - \omega^1_{it} &= \left\{ \left(\frac{\lambda^{S\prime}_{iit}}{\lambda^{M\prime}_{iit}} \right)^{-\rho/\alpha} - \left(\frac{\lambda^S_{iit}}{\lambda^M_{iit}} \right)^{-\rho/\alpha} \right\} \frac{\mathcal{K}^S_{it}(H)}{\mathcal{K}^M_{it}} \\ &= \left(\frac{\lambda^S_{iit}}{\lambda^M_{iit}} \right)^{-\rho/\alpha} \left\{ \left(\frac{\widehat{\lambda}^S_{iit}}{\widehat{\lambda}^M_{iit}} \right)^{-\rho/\alpha} - 1 \right\} \frac{\mathcal{K}^S_{it}(H)}{\mathcal{K}^M_{it}} \end{aligned} \tag{E.4}$$

Furthermore, (22) implies that:

$$\varsigma_{it}^{M}(H) = \frac{1}{1 + \left(\frac{\mathcal{K}_{it}^{S}(H)}{\mathcal{K}_{it}^{M}}\right)\left(\frac{\lambda_{iit}^{S}}{\lambda_{iit}^{M}}\right)^{-\rho/\alpha}} \tag{E.5}$$

Combining them yields:

$$\frac{\varpi_{it}^{1\prime} - \varpi_{it}^{1}}{1 + \varpi_{it}^{1}} = \left[1 - \varsigma_{it}^{M}(H)\right]\left\{\left(\frac{\widehat{\lambda}_{iit}^{S}}{\widehat{\lambda}_{iit}^{M}}\right)^{-\rho/\alpha} - 1\right\} \tag{E.6}$$

Analogously, for ϖ_{it}^{2}, we obtain:

$$\frac{\varpi_{it}^{2\prime} - \varpi_{it}^{2}}{1 + \varpi_{it}^{2}} = \left[1 - \varsigma_{it}^{M}(N)\right]\left\{\left(\frac{\widehat{\lambda}_{iit}^{S}}{\widehat{\lambda}_{iit}^{M}}\right)^{-\rho/\alpha} - 1\right\} \tag{E.7}$$

Plugging this into (E.3), we finally obtain (25) in the main text.

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