Internal Migration Adjustment in Large Crises*

Jaedo Choi
Federal Reserve Board

January, 2024

Abstract

This paper studies internal migration adjustment during the South Korean 1997 crisis, and its aggregate and regional impacts. I find that there were increases in migration inflows to regions specializing in sectors that experienced larger expansion during the post-crisis recovery, with increased employment in these regions. I develop a dynamic spatial model of migration and trade. Due to sudden shocks induced by the crisis, initial labor is misallocated spatially across regions, and migration mitigates this misallocation. At the aggregate level, higher mobility increases sectoral labor reallocation, raises real GDP growth, and reduces welfare loss, while mitigating regional distributional consequences.

Keywords: large crises, migration, spatial misallocation
JEL Codes: F16, F31, R23

*This paper was previously circulated as "Internal Migration, Sectoral Reallocation, and Large Devaluation." We thank discussants Fernando Leibovici and Runjuan Liu for insightful comments and suggestions. I would like to thank Maria Aristizábal-Ramírez, Costas Arkolakis, Dominick Bartelme, Samuel Bazzi, Andreas Blanco, Matilde Bombardini, Barthélémy Bonadio, Kerem Cosar, Kirill Borusyak, Agostina Brinatti, Ariel Burstein, Jaesung Choi, Jaerim Choi, Javier Cravino, Kyle Handley, James Harrigan, Manho Kang, Gaurav Khanna, Munseob Lee, Andrei Levchenko, John McLaren, Peter Morrow, Dávid Nagy, Heitor Pellegrina, Nishaad Rao, Jagadeesh Sivadasan, Sebastian Sotelo, Linda Tesar, Jing Zhang, and seminar participants at EIIT, KIEP, Michigan, SCIEA, and Virginia for helpful comments and discussions. The views expressed in this paper are my own, and do not represent the views of the Board of Governors of the Federal Reserve, nor any other person associated with the Federal Reserve System. `E-mail:` jaedo.choi@frb.gov.

1 Introduction

Large crises are characterized by significant drops in TFP and trade adjustment due to exchange rate depreciations, with asymmetric sectoral effects. These sudden shocks from the crises, coupled with variations in regional industrial composition, result in spatial misallocation of labor across regions at the onset of crises. Spatial reallocation of labor during post-crisis recoveries has a potential to boost total output. Migration to regions experiencing better post-crisis conditions can alleviate this misallocation, but any frictions to migration impede the reallocation process. In emerging market economies, where large crises are more frequent, the migration channel is particularly relevant due to their higher migration frictions.[1]

This paper studies how internal migration responded to the South Korean 1998 crisis and its aggregate and regional impacts. My contributions are twofold. First, I provide novel empirical evidence on the reallocation of labor through migration. I find increased migration flows to regions specializing in sectors that experienced large expansion during the post-crisis recovery, and increased employment in these regions. Second, I build a model to quantitatively assess the effects of the migration channel on real GDP and welfare at both aggregate and regional levels.

Exploiting cross-sectional variation in industrial composition, I empirically document migration and employment responses to local labor market shocks induced by the crisis. I find regions with relatively larger labor demand shocks exhibited increased migration inflows and employment after the crisis. I regress changes in migration inflows (outflows) at the pair level on the "Bartik" local labor market shocks of destination (origin) fixed effects. The Bartik shock is constructed by interacting initial industry employment shares and national-level changes in gross output, with higher values corresponding to better local labor market conditions. I find that migration inflows (outflows) of a region increased by 6% (decreased by 5%) 3 years after the crisis, compared to another region with one standard deviation lower Bartik shock. Event-study specifications confirm the crisis-induced migration adjustments, showing no pre-trends. These findings remain robust even with additional controls, such as regional exposure to the balance sheet effects and unemployment rates. Using a similar empirical approach, I find regions, which received more migration inflows, also experienced larger employment increases.

These findings motivate the model. I build a dynamic spatial general equilibrium model with forward-looking migration and trade. South Korea is modeled as a small open economy. The crisis is formulated in a reduced-form fashion as five exogenous time-varying shocks: productivity, labor supply, foreign demand, import price, and trade deficit shocks. While simple, these shocks capture prevalent features of emerging market economies after large crises, as documented in the previous literature–namely, substantial drops in TFP, regional or sectoral heterogeneity in degree of labor market frictions, export expansions, collapses in imports, and rapid declines in trade deficits.

Households make decisions on which sectors to work in (sectoral labor supply) and where to

[1] For example, Bryan and Morten (2019) document higher internal migration frictions in Indonesia than in the US.

live (migration). They contain a continuum of workers. Each worker receives idiosyncratic labor efficiency units across different sectors. Given region-sector wages and workers' idiosyncratic labor units, households optimally allocate their workers across sectors to maximize the total sum of wages of their workers, akin to the Roy model of sector choice. These decisions determine sectoral labor supply within regions, conditional on population. Migration decisions are modeled as dynamic discrete choices. Workers choose locations based on real income, option values of being in one region, amenities, and non-monetary migration frictions measured in terms of utility. In response to the shocks, households optimally make migration decisions, which helps alleviate the initial spatial misallocation.

The model is calibrated to data at the region-sector level. I derive a regression model from the model and estimate the migration elasticity using the IV strategy. The IV exploits cross-sectional variations in industrial composition, similar to those used for the empirical analysis. I calibrate exogenous shocks by exactly fitting the model to the data. Region-sector gross output, sectoral producer price indices (PPIs), and aggregate real GDP growth pin down productivity shocks. Region-sector employment shares pin down labor supply shocks, while export and import shares pin down foreign demand and import cost shocks, respectively. Trade deficits are directly taken from the data. The dynamic equilibrium path of the model reproduces the annual data on these variables.

The calibrated model successfully replicates the two empirical findings, when running the same specifications used for the empirical analysis using the model-generated data, as non-targeted moments. The labor supply shocks are the most important factor in replicating these findings. When turning off the labor supply shocks, the model fails to generate the same patterns observed in the empirical findings. These results highlight the importance of considering labor supply side in understanding the dynamics of employment and migration flows.

Using the calibrated model, I conduct two counterfactual analyses. First, I assess how the economy would have adjusted differently in response to the crisis depending on varying levels of migration mobility. I compare the transition paths of the baseline economy, where migration mobility aligns with observed flows in the data, and with those of counterfactual economies. These counterfactual economies have different migration mobility levels, constructed by feeding in migration friction shocks. I consider hypothetical temporary changes in mobility levels rather than specific policies. However, these hypothetical changes can be potential outcomes of migration policies during the crisis, such as temporarily subsidizing rural workers to urban regions. I find that at the aggregate level, higher mobility led to greater sectoral labor reallocation and real GDP growth, implying that migration mitigated the initial misallocation and increased total output during the recovery.

Second, I evaluate how welfare effects vary depending on mobility levels. For each mobility level, I compare the baseline and the counterfactual in which the crisis did not occur. Because both the baseline and counterfactual economies have the same mobility level, the exercise focuses on welfare changes due to the crisis rather than direct welfare effects of different mobility levels. We construct this no-crisis counterfactual by turning off the exogenous shocks. Higher mobility decreased the aggregate welfare loss due to the crisis and mitigated regional distributional consequences, because it provided households in regions that fared worse due to the crisis with the opportunity to move to other regions.

The quantitative findings suggest that migration policies can be one of the policy options for policymakers to stimulate economic growth during post-crisis recoveries in emerging market economies. While the framework does not explicitly incorporate the costs of increasing mobility, the quantitative exercises provide insights into the benefits of enhanced mobility. This information can be valuable for policymakers, especially considering that many real-world policies target observed outcomes after large crises, such as real GDP growth.

Related literature This paper contributes to several strands of the literature. First, I contribute to the large literature on consequences of large crises (see among many others, Aguiar, 2005; Burstein et al., 2005, 2007; Alessandria et al., 2010; Pratap and Urrutia, 2012; Gopinath and Neiman, 2014; Kim et al., 2015; Chaney, 2016; Blaum, 2018; Bonadio et al., 2020; Ates and Saffie, 2021; Blanco et al., 2022b; Auer et al., 2022). I contribute to this literature by studying internal migration responses to the crisis and the spatial dimensions of the crisis. Alessandria et al. (2020) and Kohn et al. (2020) document sluggish recoveries and export adjustments after crises due to sluggish export adjustment due to sunk export entry costs and financial frictions, respectively. Queralto (2020) studies slow recoveries due to financial frictions and decline in innovation efforts in the context of the South Korean crisis. I show that migration frictions can be one channel that leads to such sluggish adjustment and recoveries. Drenik (2016) and Blanco et al. (2022a) study distributional effects of the 2002 Argentinian devaluation episode due to heterogeneous levels of nominal rigidities across sectors and labor market frictions. Cravino and Levchenko (2017) and Drenik et al. (2018) study distributional consequences of large devaluations through the cost of living and nominal net asset positions, respectively. I document regional distributional consequences of the crisis due to heterogeneous industrial composition. Methodologically, similar to Eaton et al. (2016) who study forces behind the Great Recession and ensuing recovery using the quantitative trade model, I calibrate shocks by exactly fitting the model to the data.

Second, this paper is related to the quantitative spatial and trade literature on migration (Morten and Oliveira, 2018; Bryan and Morten, 2019; Fan, 2019; Tombe and Zhu, 2019; Hao et al., 2020; Imbert and Papp, 2020; Ma and Tang, 2020; Pellegrina and Sotelo, 2021; Lagakos et al., 2023). Methodologically, my model builds on the quantitative dynamic spatial equilibrium model with discrete choices developed by Artuc et al. (2010) and Caliendo et al. (2019). Using the similar frameworks, Dix-Carneiro (2014), Traiberman (2019), and Artuc et al. (2021) study transmissions of trade shocks and Caliendo et al. (2021) study the labor market integration of the EU. I apply this framework to study internal migration responses to the crisis and show that migration mobility is an important adjustment mechanism. Similar to Bryan and Morten (2019), I consider hypothetical reductions in migration frictions, rather than specific policies as in Tombe and Zhu (2019) and Fan

(2019). Unlike previous papers which focus on long-run consequences of migration frictions, such as welfare and TFP, this paper studies how migration frictions affect short-run transitional adjustment in the short-run after the crisis.

Third, this paper contribute to the literature that studies internal migration adjustments to local labor market conditions, pioneered by Blanchard and Katz (1992), (see, among many others, Topalova, 2010; Autor et al., 2013; Kovak, 2013; Monras, 2015, 2020; Cadena and Kovak, 2016; Hakobyan and McLaren, 2016; Dix-Carneiro and Kovak, 2017; Kondo, 2018; Dix-Carneiro and Kovak, 2019; Benguria et al., 2018; Greenland et al., 2019; Adão et al., 2020; House et al., 2020). Previous papers have studied more persistent local labor demand shocks, such as long-run Bartik-style shocks, commodity super-cycles, the China shock, and trade liberalization episodes. In this paper, I study short-run migration responses to more transitory shocks due to the crisis.

Structure The structure of this paper is as follows. Section 2 describes the data used for the empirical and quantitative analysis and the background on the South Korean crisis. Section 3 presents empirical evidence on changes in migration flows and employment after the crisis. Section 4 presents a quantitative model to quantify the effects of the migration channel and the calibration procedure of othe model. Section 5 presents quantitative results. Section 6 concludes.

2 Data and Background

2.1 Data

The final data set contains information on region-sector employment shares, region-sector gross output, region-to-region migration flows, regional population, sectoral trade, and other sectoral variables. The sample period spans from 1995 to 2002, the year in which the Korean government paid back the bailout loan from the IMF. I aggregate data to 54 regions, based on their electoral district, and 15 sectors. This aggregation ensures that each region has positive employment for all 15 sectors. See Appendix Section A for more details on the construction of the final data set.

Region-sector employment shares I construct region-sector employment shares from the Census on Establishment which covers the universe of formal establishments with one or more employees at a finely disaggregated geographic level for all sectors.[2] The data set has information on geographical locations, sectors, and employment of establishments. I compute region-sector shares by summing up employment across establishments within region-sectors and dividing the sum by total regional employment.

Region-sector gross output I construct region-sector gross output by combining the Census of Establishment, and state-level sectoral gross output, and the IO tables from the WIOD 2013 release (Timmer et al., 2015). I allocate national sectoral gross output from the WIOD across 16 states using the state-level gross output data obtained from Statistics Korea. Within each state-sector, I allocate

[2] On average, approximately 2.9 million establishments are covered by this data set across the sample period.

Table 1: Descriptive Statistics

Variable	Mean	SD	Median
Overall mfg. emp. share	0.28	0.13	0.24
Top 5 export-intensive mfg. emp. share	0.19	0.12	0.17
Outflow migration rate	0.11	0.03	0.10

Notes. This table reports the descriptive statistics of the data set. $N = 432$. There are 15 sectors and 54 regions. The sample period is between 1995 and 2002.

region-sector gross output using region-sector employment from the Census of Establishment.

Region-to-region migration flows and regional population I obtain datasets on the number of internal migrants between regions and regional populations from Statistics Korea. I calculate migration flows as the total number of migrants between origin and destination regions divided by the lagged populations of the origin regions. I restrict the sample to individuals aged between 20 and 55 to focus on the working-age population and capture the demographic group most likely to engage in labor-related migration.

Sectoral data and IO tables I obtain sectoral import and export data and IO tables between 1995 and 2002 from the WIOD and, before 1995, from the Bank of Korea. I aggregate countries except for South Korea as the rest of the world. Sectoral PPIs are obtained from the OECD STAN Database.

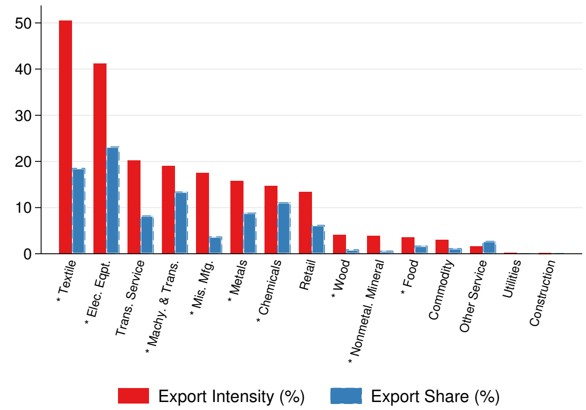
Descriptive statistics Table 1 presents the descriptive statistics of the final dataset. The average employment shares in the overall and the five most export-intensive manufacturing sectors were 19% and 28%, respectively. On average, 11% of people moved to different regions annually. When aggregating 54 regions up to 16 states, which is more comparable with the average land size of US counties, to get a sense of mobility in South Korea, the average outflow rate is 7.2%. This rate is approximately 1 percentage point higher than the annual inter-county migration rates reported in Molloy et al. (2011).

2.2 Stylized Facts

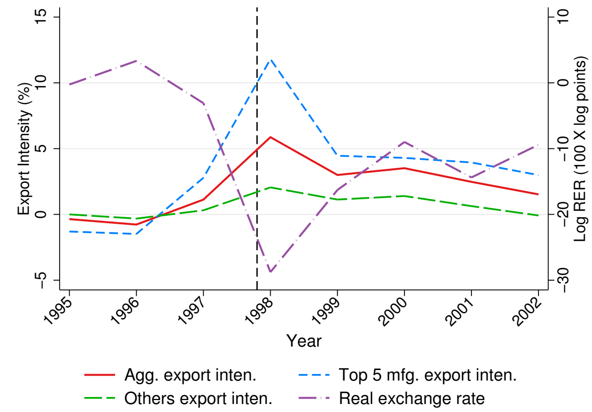
I present three stylized facts about the crisis, summarized in Figure 1.

Fact 1. Large increases in exports with sectoral heterogeneity I first define sectoral export-intensity as the share of sectoral exports to sectoral gross output. Panel A shows substantial variation in the export-intensities, with manufacturing sectors demonstrating higher export-intensity and export shares. Based on the export-intensities, I define the top 5 most export-intensive manufacturing

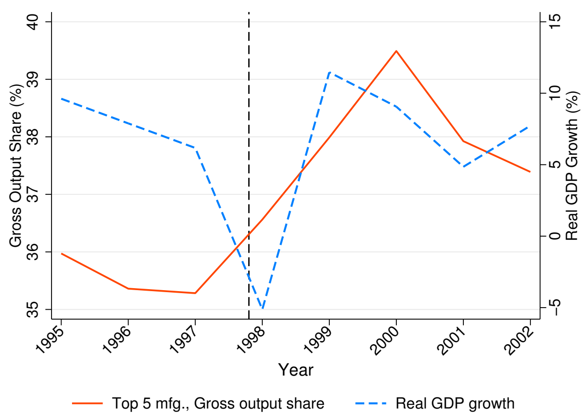
Figure 1. Stylized Facts after the South Korean 1997 Crisis



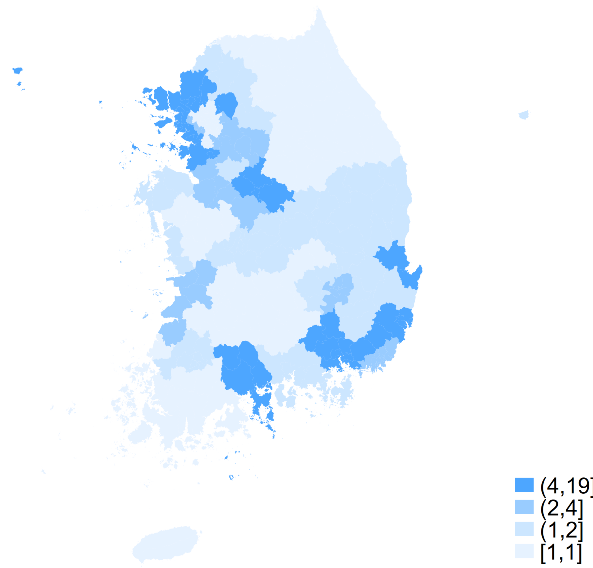
A.Sectoral Heterogeneity in export-intensity



B. export-intensity & Log RER



C. Gross output share &
Real GDP growth



D. top 5 mfg. emp share

Note. Panel A shows the sectoral export-intensity and export shares in 1994. An asterisk * denotes manufacturing sectors. In Panel B, the export-intensities and log real exchange rate around the crisis are plotted, distinguishing overall sectors (red solid line), the top 5 most export-intensive manufacturing sectors (blue dashed line), and the remaining sectors (green long-dashed line). The purple long-dashed line represents the log real exchange rate multiplied by 100. Each export-intensity is normalized by the median between 1995 and 1997. Panel C displays the share of gross output from the top 5 most export-intensive manufacturing sectors to total gross output (red solid line) and real GDP growth (blue dashed line). Panel D plots employment shares of the top 5 most export-intensive manufacturing sectors in 1994. Regions are colored based on quartiles, with darker shades indicating higher values sectors.[3]

With a 26% depreciation in the real exchange rate, the aggregate export-intensity, defined as the share between aggregate exports to aggregate gross output, increased from 15% in 1997 to 19% in 1998, remaining approximately 2 percentage points higher in the subsequent years (Panel B). This aggregate increase is primarily attributed to heightened export-intensities of the top 5 sectors. Normalizing the export-intensities by the median between 1995 and 1997 for ease of comparison, the intensity of the top 5 sectors increased by 4.9 (2.2) percentage points in 1998 (2000) relative to 1997, surpassing the other sectors.

Fact 2. Large drop in real GDP and expansion of export-intensive sectors during the recovery After the crisis, annual real GDP growth declined from 5.2% in 1997 to −5.8% in 1998 (Panel C). Since 1999, as real GDP growth rebounded to pre-crisis levels, the gross output shares of the top 5 sectors gradually increased, peaking in 2000, accompanied with their export expansion (Panel B). This fact implies that contributions to the aggregate growth varied across sectors, with a particularly important role played by the top 5 in driving the recovery.

Fact 3. Regional heterogeneity in industrial composition The top 5 sectors were geographically concentrated in a few regions, as illustrated in Panel D, which shows regional variation in employment shares of the top 5 sectors. This highlights the geographical concentration of these sectors in the northwestern and southeastern regions. The variation in regional industrial composition implies that the crisis could have differential impacts across regions, and contributions to aggregate growth during the recovery could have been driven asymmetrically across regions.

Discussion After the substantial decline in real GDP, the recovery period witnessed a notable contribution from more export-intensive sectors. This contribution is attributed, in part, to their export expansion, which may signify factors such as faster productivity growth or increased foreign demand due to depreciation. Given the asymmetric impacts of the crisis across regions and sectors, workers may have migrated to regions specializing in sectors that experienced larger expansion during the recovery. In the next section, I leverage cross-sectional variation in industrial composition to provide empirical evidence supporting this migration pattern.

3 Empirical Evidence on Spatial Reallocation of Labor

3.1 Migration flow

I first examine examine migration responded after the crisis. I consider first-difference specifications for changes in migration inflows and outflows between 1997 and 2000, which examine how migration

[3]The top 5 sectors include textiles, electrical equipment, machinery and transportation equipment, metals, and chemicals. The miscellaneous manufacturing sector, despite having higher export-intensity than some included sectors, was not classified among the top 5 due to its low export shares and ambiguous classification.

responded to destination m's and origin n's local labor market shocks, respectively:

$$\triangle \ln \mu_{nm} = \beta \text{Bartik}_m + \mathbf{X}_m' \boldsymbol{\gamma} + \delta_n + \triangle \epsilon_{nm}, \quad \triangle \ln \mu_{nm} = \beta \text{Bartik}_n + \mathbf{X}_n' \boldsymbol{\gamma} + \delta_m + \triangle \epsilon_{nm}. \tag{3.1}$$

Dependent variables are changes in migration flows from region n to m, defined as a share of total migrants from region n to m relative to lagged population in n, between 1997 and 2000. Bartik_m is a standardized Bartik-style local labor market shock, which will be discussed below. $\mathbf{X}_n$ is region n's observables. δ_n are regional fixed effects. ϵ_{nm} are the error terms. Any time-invariant pair characteristics, such as distance, are differenced out. Standard errors are two-way clustered at both origin and destination levels. Zero observations are not an issue because only 2 out of 2916 observations are dropped due to zero values. Note that the specification is at the migration pair-level, incorporating the bilateral nature of location choices.[4]

The Bartik shock is constructed as the employment-weighted sectoral growth of gross output excluding region n's gross output:

$$\text{Bartik}_n = \sum_{j=1}^{J} \frac{\text{Emp}_{nj,94}}{\sum_{j'=1}^{J} \text{Emp}_{nj',94}} \times \triangle \text{Gross Output}_{(-n)j,00}. \tag{3.2}$$

$\triangle$Gross $\text{Output}_{(-n)j,00}$ represents the sectoral growth of gross output excluding region n between 1997 and 2000. The higher Bartik shock implies that regions initially had higher employment shares in sectors with larger expansion after the crisis, and therefore, experienced relatively better labor market conditions. $\triangle$Gross $\text{Output}_{(-n)j,00}$ is related to sector j's underlying productivity shocks, export expansion, or its sector-specific frictions that prevent from it growing during the crisis.

Columns 1 and 9 of Table 2 present the estimated coefficients without additional controls. The coefficients are statistically significant at the 1% for both inflows and outflows. There were 9% higher migration inflows to a region compared to the other with one standard deviation lower $\text{Bartik}_{m,94}$. Also, there were 6% fewer outflows from this region.

In columns 2 and 10, I include the initial log employment in 1994 to account for heterogeneous trends dependent on the size of employment. In columns 3 and 11, I control for pre-crisis changes in migration flows between 1995 and 1996 ($\triangle \ln \mu^{pre}_{nm,96} = \ln \mu_{nm,96} - \ln \mu_{nm,95}$) to address potential confounding preexisting trends, following Dix-Carneiro and Kovak (2017). The pretrend controls are statistically insignificant.

Previous studies like Kim et al. (2015) and Queralto (2020) documented negative balance sheet effects post-crisis. I construct a variable that captures regional exposure to the effects and include it in the regression. I first construct sector-level exposure by averaging firm-level exposures within

[4] Borusyak et al. (2022) demonstrate that conventional migration regression at the region level, which ignores the bilateral nature, may lead to a violation of the SUTVA condition.

Table 2: OLS First-Difference. Migration Responses to the Crisis

Spec.	Inflows								Outflows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$\text{Bartik}_{m(n),94}$	0.09***	0.09***	0.09***	0.08***	0.08***	0.09***	0.08**	0.07**	−0.04***	−0.04***	−0.04***	−0.06***	−0.04***	−0.04***	−0.04***	−0.04***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
$\ln \text{Emp}_{m(n),94}$		−0.01						−0.01		−0.04***						−0.04***
		(0.02)						(0.02)		(0.01)						(0.01)
$\triangle \ln \mu^{pre}_{nm,96}$			0.02					0.01			0.02					0.01
			(0.04)					(0.04)			(0.04)					(0.03)
$\text{RegBS}_{m(n),94}$				−0.00				−0.01				−0.02				−0.01
				(0.02)				(0.02)				(0.02)				(0.01)
$\triangle \ln \text{Unemp}_{m(n),00}$					−0.08**			−0.07*					0.01			0.02
					(0.04)			(0.04)					(0.02)			(0.02)
$\text{IndDiff}_{nm,94}$						−0.00		−0.00						−0.00		−0.01
						(0.01)		(0.01)						(0.01)		(0.01)
$\text{Amenity}_{m(n),94}$							−0.02	−0.02							0.01	0.00
							(0.01)	(0.01)							(0.01)	(0.01)
Origin FE	✓	✓	✓	✓	✓	✓	✓	✓								
Dest. FE									✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.16	0.16	0.16	0.16	0.18	0.16	0.17	0.19	0.31	0.32	0.31	0.31	0.31	0.31	0.31	0.32
# Cluster (Origin)	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54
# Cluster (Dest.)	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54
N	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914

Note. Standard errors, two-way clustered at the origin and destination levels, are in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. The table reports the OLS estimates of eq. (3.1). The dependent variables are changes in log migration shares. In columns 1-8 and 9-16, the regression specifications are $\triangle \ln \mu_{nmt} = \beta \text{Bartik}_{m,94} + \mathbf{X}'_{mt}\boldsymbol{\gamma} + \delta_n + \triangle\epsilon_{nmt}$ and $\triangle \ln \mu_{nmt} = \beta \text{Bartik}_{n,94} + \mathbf{X}'_{nt}\boldsymbol{\gamma} + \delta_m + \triangle\epsilon_{nmt}$, respectively. $\text{Bartik}_{n(m)t_0}$ is the Bartik shock. Column 2 and 10 include log initial employment of destination and origin regions, respectively. Columns 3 and 11 include changes in migration flows between 1995 and 1996. Columns 4 and 12 include destination and origin's regional exposure to the balance sheet effect (eq., 3.3). Columns 5 and 13 include destination and origin's changes in log unemployment rate between 1995 and 2000. Columns 6 and 14 include differences of industrial composition between origin and destination regions (eq., 3.4). Columns 7 and 15 include destination and origin's changes in the amenity index between 1995 and 2000. Columns 8 and 16 include all additional variables jointly. Columns 1-8 and 9-16 include origin and destination fixed effects, respectively.

sectors, with weights determined by firm-level employment:

$$\text{BS}_{j,95} = \sum_{f \in \mathcal{F}_{j,95}} \frac{\text{Emp}_{fj,95}}{\sum_{f \in \mathcal{F}_{j,95}} \text{Emp}_{fj,95}} \times \frac{\text{Net foreign debt}_{fj,95}}{\text{Net worth}_{fj,95}}.$$

The net foreign debt ratio $\frac{\text{Net foreign debt}_{fj,95}}{\text{Net worth}_{fj,95}}$ represents the 1995 ratio of net foreign debt to net worth. This ratio was proposed by Kim et al. (2015) and computed using firm-level data from KIS-VALUE, indicating increased financial burdens for firms with larger foreign debts.[5] Then, I take the employment-weighted average at the regional level:

$$\text{RegBS}_{n,94} = \sum_{j=1}^{J} \frac{\text{Emp}_{nj,94}}{\sum_{j=1}^{J} \text{Emp}_{nj,94}} \times \text{BS}_{j,94}. \tag{3.3}$$

Regions with higher employment in sectors exhibiting larger $\text{BS}_{j,94}$ are considered more exposed to the balance sheet effect. Controlling for these balance-sheet effects does not alter the results, suggesting that lower growth in gross output in the Bartik shock may already reflect the impact of the balance sheet effects.

During the crisis, the unemployment rate rose from 2.6% to 7.0% between 1997 and 1998. This large change in unemployment could potentially influence migration flows. To address this concern, I control for the changes in the log regional unemployment rates between 1995 and 2000, $\triangle \ln \text{Unemp}_{m(n),00} = \ln \text{Unemp}_{m(n),00} - \ln \text{Unemp}_{m(n),95}$, obtained from Population Census. Because the regional unemployment rate in 1997 is unavailable, I use the 1995 level as a proxy for it, assuming stability between 1995 and 1997.[6] Columns 5 and 13 report the results with the unemployment controls. Although unemployment rate controls are statistically significant at the 5% level for migration inflows, the Bartik coefficients remain stable.

With potential costs associated with sectoral reallocation, workers may prefer migrating to regions with a similar industrial composition to their current residence.[7] To capture such effects, I construct a variable that measures the differences in industrial composition between two regions, using the Mahalanobis distance between the initial employment shares:

$$\text{IndDiff}_{nm,94} = \sqrt{(\boldsymbol{\lambda}_{n,94} - \boldsymbol{\lambda}_{m,94})' \boldsymbol{\Sigma}^{-1} (\boldsymbol{\lambda}_{n,94} - \boldsymbol{\lambda}_{m,94})}. \tag{3.4}$$

$\boldsymbol{\lambda}_{nt_0}$ is a $J \times 1$ vector representing region n's employment shares, and $\boldsymbol{\Sigma}^{-1}$ is a sample covariance

[5] Kim et al. (2015) also use KIS-VALUE to compute firm-level exposure to the balance sheet effect after the South Korean crisis. It covers firms with assets above 3 billion Korean Won (2.3 million USD in 2023). It is similar to US Compustat and has detailed financial information but it includes medium-sized firms that are not publicly traded. Net foreign debt is foreign currency-denominated debt minus foreign currency denominated assets and net worth is total assets minus total liabilities.

[6] This assumption aligns with the stable aggregate unemployment rate around 2.2% between 1994 and 1996.

[7] For example, Artuc et al. (2010), Dix-Carneiro (2014), and Traiberman (2019) have documented sizable mobility costs across sectors and occupations.

matrix. Columns 6 and 14 report the estimates with $\text{IndDiff}_{nm,94}$.

Concerns about omitted variable bias can arise if amenities respond to local population and are correlated to the Bartik shocks (e.g., Diamond, 2016). Despite the short-run time horizon mitigating this concern, I provide formal evidence that it is unlikely to be a significant issue. Following Diamond (2016), I construct an amenity measure as the first principal component of bundles of observable amenities in 1995 and 2000, and include its difference between 1995 and 2000 as a control.[8] Columns 7 and 15 report the estimates with the amenity controls.

In columns 8 and 16, I control for all additional controls jointly. The estimates stay within one standard deviation from the estimates without any controls.

The results are robust to alternative forms of clustering which allows spatial correlations across nearby regions (Conley, 1999; Colella et al., 2021) and across regions with similar initial shares (Adão et al., 2019). Also, using a double LASSO control selection (Belloni et al., 2014), I flexibly select controls to be included among the additional controls and their polynomials up to the third order, and obtain the similar results (Appendix Table B6).

Event study As shown in Panel B of Figure 1, the top 5 sectors experienced the largest gross output growth, explaining most of the variation in the first difference specifications. If there were pretrends for regions with higher top 5 shares before the crisis, the estimates from the first-difference specifications can be driven by these pretrends. To investigate pretrends and dynamic effects, I employ the following event-study specifications for migration inflows and outflows:

$$\ln \mu_{nmt} = \sum_{\tau=-3}^{4} \beta_\tau (D_t^\tau \times \text{Empsh}_{m(n)t_0}^{\text{top5}}) + \sum_{\tau=-3}^{4} (D_t^\tau \times \mathbf{X}_{m(n)t_0})' \boldsymbol{\gamma}_\tau + \delta_{nm} + \delta_{n(m)t} + \epsilon_{nmt}. \tag{3.5}$$

$\text{Empsh}_{m(n)t_0}^{\text{top5}}$ is the initial top 5 employment shares in region m (or n). D_t^τ are the event time dummies. δ_{nm} are time-invariant pair fixed effect. $\delta_{n(m)t}$ are origin-year (or destination-year) fixed effects. Time-varying observables $\mathbf{X}_{m(n)t_0}$ include the initial log employment, amenity index, log unemployment, and the regional balance sheet exposure, all interacted with the event time dummies. I normalize β_{-1} to zero. Standard errors are two-way clustered at the origin and destination levels.

Figure 2 present the estimates. The magnitudes of the estimated coefficients in 2000 aligns with those from the first difference specifications. No pretrends are observed for migration outflows. However, for migration inflows, there are pretrends in the opposite direction to the estimates. This implies that even if they persisted after the crisis, they would bias down the coefficients for migration inflows

[8] It includes the number of retail establishments per capita for the retail environment; the number of establishments in education service per capita for the education environment; shares of workers using public transportation for commuting for transportation infrastructure; the number of factories per capita for the environment; and shares of white collar occupation workers and the number of business service establishments per capita for the quality of jobs. All these variables had positive loadings except for the number of factories, which is likely to exert a negative influence on the local environment (Appendix Table B2).

Figure 2. Event Study. Migration Responses to the Crisis

A. Inflows B. Outflows

Note. Panels A and B illustrate the estimated β_τ in eq. (3.5) for the top 5 employment shares of destination and origin, respectively. The 95% confidence intervals, based on standard errors two-way clustered at the origin and destination levels, are reported. The black dashed line indicates the year of the crisis. The dependent variables are log migration shares between origin and destination regions. The coefficients in 1997 are normalized to zero. Panel A includes origin-year and pair fixed effects, while Panel B includes destination-year and pair fixed effects. Both panels' specifications include the initial log employment in 1994, the initial log unemployment, and the amenity index in 1995, as well as the initial regional balance sheet exposure (eq., 3.3) of destination and origin regions, interacted with the event-time dummies.

and the estimates would be lower bounds for true impacts. Nonetheless, due to these pretrends, as a robustness check, I investigate sensitivity to potential violations of pretrends following Rambachan and Roth (2023).[9] The estimated coefficients remain robust to potential deviations (Appendix Figure **??**).

Commuting To address concerns about commuting effects due to the granularity of spatial units, I conduct two robustness exercises.[10] First, I examine changes in bilateral commuting flows between 1995 and 2000, computed from the population census. I find no significant effects (Appendix Table B3). This suggests that the migration estimates are unlikely to be affected by commuting margins at the current level of aggregation. Second, I rerun the specifications after dropping pairs with distances smaller than 62 miles (100km). The subsample, not subject to commuting margins, yields coefficients close to the baseline estimates (Appendix Table B4).

[9] Following their notations, $\triangle^{SD}(M)$ represents the potential set of deviations $\triangle^{SD}(M) := \{\delta : |(\delta_{t+1} - \delta_t) - (\delta - \delta_{t`1})| \leq M, \forall t\}$. Their methodology relaxes the parallel trends assumption by allowing deviations from linearity up to a parameter M, with larger values of M leading to wider confidence sets. Appendix Figure B9 displays the 90% confidence intervals associated with different values of M, with the maximum values of M set to the standard errors associated with the estimates in 2000.

[10] South Korea is similar in size to Indiana in the US and regions in my analysis are, on average, 66% the size of US counties, smaller than the average US commuting zone.

Shift-share diagnostics The aforementioned specifications are based on a shift-share research design. If the exogeneity of the initial shares, conditional on the controls and fixed effects, holds, the estimates can be causally interpreted–the setup studied by Goldsmith-Pinkham et al. (2020).[11] In particular, the Rotermberg weights are highly skewed and the top 5 sectors explain more than 96% of the positive weights of the estimators (Appendix Tables B8 and B7). This implies that the estimates can be sensitive to confounding factors that affect regions with large employment shares in these top 5 sectors. Following the diagnostic proposed by Goldsmith-Pinkham et al. (2020), I correlate the top 5 employment shares to other observables. I do not find statistically significant correlations with employment shares in the top 5 sectors that were most exposed to the balance sheet effects, unemployment rates, and amenity in the initial year. This result alleviates the concern for confounding factors.

3.2 Regional employment

I next demonstrate that regions with larger migration inflows after the crisis experienced larger employment increases. I run

$$\triangle y_n = \beta \text{Bartik}_n + \mathbf{X}_n' \boldsymbol{\gamma} + \epsilon_n. \tag{3.6}$$

I consider three dependent variables: changes in log total employment, log employment in the top 5 sectors, and log employment in the remaining non-top 5 sectors between 1997 and 2000. To examine dynamic effects and pretrends, I also run the following event study specification:

$$y_{nt} = \sum_{\tau=-3}^{4} \beta_\tau (D_t^\tau \times \text{Empsh}_{nt_0}^{\text{top5}}) + \sum_{\tau=-3}^{4} (D_t^\tau \times \mathbf{X}_{nt_0})' \boldsymbol{\gamma}_\tau + \delta_n + \delta_t + \epsilon_{nt}. \tag{3.7}$$

For both specifications, I include the similar set of observables used for the migration analysis, depending on specifications, including the regional balance sheet exposure and the changes in log unemployment rates and the amenity index.[12] I weight regression weights by each region's initial total employment.

Table 3 reports the estimates from the first-difference specification. A region experienced 4% higher overall employment growth compared to another with one standard deviation lower Bartik shock. This region also experienced not only higher employment in the top 5 sectors, but also that in the remaining sectors, although the estimates for the top 5 employment were imprecisely estimated, possibly due to the small number of observations. The event study results reconfirm the results (Figure 3). Regions with higher initial top 5 shares, which experienced larger Bartik shocks, also

[11] Because there are only 15 sectors, I rely on the exogeneity of the initial shares rather than the assumption where shocks are as-good-as-randomly assigned (Borusyak et al., 2022).

[12] I did not include the initial log employment as it is used as a dependent variable. Also, IndDiff_{mnt_0} is well-defined only at the pair level.

Table 3: OLS First-Difference. Employment Responses to the Crisis

Dep.	$\triangle$ log total emp.		$\triangle$ log emp., top 5		$\triangle$ log emp., others	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Bartik}_{n,00}$	0.05^{***}	0.04^{**}	0.07^{**}	0.06	0.04^{***}	0.03^{**}
	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)
$\triangle y_{n,97}$		0.48		-0.13		0.52
		(0.34)		(0.32)		(0.35)
$\text{RegBS}_{n,94}$		-0.00		-0.01		-0.01
		(0.01)		(0.03)		(0.01)
$\triangle \ln \text{Unemp}_{n,00}$		-0.02		-0.10^{**}		-0.01
		(0.02)		(0.04)		(0.02)
$\triangle \ln \text{Amenity}_{n,00}$		0.00		0.00		-0.00
		(0.01)		(0.01)		(0.01)
Adj. R^2	0.30	0.37	0.18	0.18	0.31	0.44
N	54	54	54	54	54	54

Note. Robust standard errors are in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. In columns 1-2, 3-4, and 5-6, the dependent variables are changes in the log total employment, the log employment in the top 5 sectors, and the log employment in the remaining sectors between 1997 and 2000. $\text{Bartik}_{n(m)t_0}$ is the Bartik shock. Columns 2, 4, and 6 include changes in dependent variables between 1995 and 1997, the regional balance sheet exposure (eq., 3.3), changes in log unemployment rates between 1995 and 2000, and changes in the amenity index between 1995 and 2000.

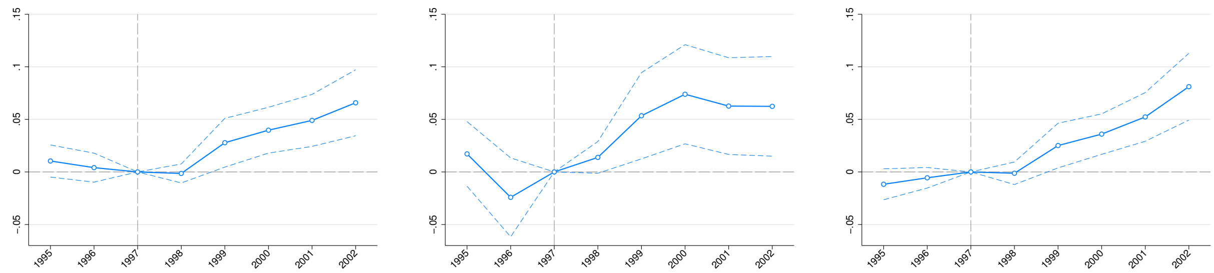
experienced higher growth in employment in both the top 5 and the remaining sectors. The top 5 employment started to increase abruptly right after the crisis, consistent with the surge in top 5 mfg. gross output shares (Panel C of Figure 1, followed by a more gradual increase of the remaining sectors. The estimates for the top 5 employment are more precisely estimated than the estimates from the first-difference specifications.

The increases of employment in the remaining sectors are consistent with local multiplier effects (Moretti, 2010). The influx of labor supply into the top 5 sectors increases labor demand from the remaining sectors. Also, a larger labor supply in the top 5 sectors will decrease overall production costs of all sectors through IO linkages due to the presence of trade frictions, thereby increasing demand for the remaining sectors. These forces generate local multiplier effects in the remaining sectors.[13]

Because both analyses of migration and employment exploit the same regional employment shares,

[13] To quantify the long-term change in local employment in nontradable sectors due to an increase in local employment in tradable sectors, Moretti (2010) estimate the following specification: $\triangle \ln \text{Emp}_n^{\text{NT}} = \beta \triangle \ln \text{Emp}_n^{\text{T}} + \epsilon_n$ where Emp_n^{NT} and Emp_n^{T} are employment in non-tradable and tradable sectors. He obtains the elasticity 0.3–0.5. Consistent with these values, when I run a similar specification for 1997–2000 using OLS or the initial top 5 employment shares as the IV, I obtain the elasticity of 0.2–0.5.

Figure 3. Event Study. Employment Responses to the Crisis



A. Log total emp. B. Log top 5 emp. C. Log non-top 5 emp.

Note. This figure illustrates the estimated β_τ in eq. (3.7). The 95% confidence intervals, based on robust standard errors, are reported. The black dashed line indicates one year before the crisis. In Panels A, B, and C, the dependent variables are log total employment, log employment in the top 5 sectors, and log employment in the remaining sectors. The coefficients in 1997 are normalized to zero. All specifications include the initial log employment, the regional balance sheet exposure (eq., 3.3), the initial log unemployment rate, and the initial amenity index, all of which are interacted with the event-time dummies. All specifications include region and year fixed effects.

they rely on the similar identifying assumption for the causal interpretation and the similar shift-share diagnostics can be applied. The OLS estimates of the first-difference specifications are robust to the alternative forms of clustering (Appendix Table B10), and the post-double-LASSO control selection (Appendix Table B11). The event-study estimates are robust to the minor violations of the parallel trend assumption (Appendix Figure B10).

4 Quantitative Framework

4.1 Model

The empirical findings suggest that there was sizable spatial reallocation of labor through migration. To quantitatively explore the general equilibrium effects and counterfactuals, I develop a dynamic spatial general equilibrium model of migration and trade.

4.1.1 Environment

The world is divided into Home and Foreign, corresponding to South Korea and the rest of the world. Home is a small open economy that takes the world import price as given but faces downward-sloping demand for its products in the international market. Home is composed of N regions, indexed by $n, m \in \mathcal{N} = \{1, \ldots, N\}$. There are J sectors, indexed by $j, k \in \mathcal{J} = \{1, \ldots, J\}$. Each region is spatially linked through costly trade and migration. Internal and international trade are subject to iceberg trade costs. For a unit of any sector j variety goods shipped from n to m for $n, m \in \mathcal{N} \cup \{F\}$ where F denotes Foreign, $d^j_{nm} \geq 1$ units have to be shipped. I normalize $d^j_{nn} = 1$, $\forall n \in \mathcal{N}$.

Each region is populated with representative households. They are forward-looking with perfect foresight and discount the future with a discount factor $\beta \in (0,1)$. They live hand-to-mouth, spending all of their income on consumption each period. They supply labor inelastically and make migration decisions subject to migration frictions. I normalize the total population to one: $L_t = \sum_{n=1}^{N} L_{nt} = 1$.

4.1.2 Production

Intermediate goods producer Each region n produces a unique sector j intermediate good variety. A representative intermediate goods producer of each region-sector produces a variety using Cobb-Douglas technology:

$$q_{njt} = A_{njt} H_{njt}^{\gamma_j^H} \prod_{k=1}^{J} (M_{njt}^k)^{\gamma_j^k}, \qquad \gamma_j^H + \sum_{k=1}^{J} \gamma_j^k = 1. \tag{4.1}$$

A_{njt} is productivity, H_{njt} is labor input, M_{njt}^k is sector k material input used by sector j, γ_j^H are labor shares, and γ_j^k is the share of sector j goods spent on intermediate input from sector k. Under cost minimization, the unit cost of production is

$$c_{njt} = \frac{1}{A_{njt}} \left(\frac{W_{njt}}{\gamma_j^H} \right)^{\gamma_j^H} \prod_{k=1}^{J} \left(\frac{P_{nkt}}{\gamma_j^k} \right)^{\gamma_j^k}, \tag{4.2}$$

where W_{njt} is region-sector wage and P_{njt} is price of intermediate inputs.

Final goods producer Final goods are non-tradable and can be used as material inputs or final consumption goods. Final goods are the constant elasticity of substitution aggregate of sector j intermediate goods from domestic regions, q_{njt}, and Foreign, q_{Fjt}:

$$Q_{njt} = \left(\sum_{m=1}^{N} q_{mjt}^{\frac{\sigma-1}{\sigma}} + q_{Fjt}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{4.3}$$

σ is the elasticity of substitution. The final goods market is perfectly competitive and free entry ensures zero profits. The associated price index is

$$P_{njt}^{1-\sigma} = \sum_{m=1}^{N} (d_{mn}^j c_{mjt})^{1-\sigma} + (d_{Fn}^j P_{jt}^F)^{1-\sigma}. \tag{4.4}$$

P_{jt}^F are import prices exogenous to the Home regions.

Trade Region n's sector j expenditure shares on intermediate goods from region m and Foreign are given by

$$\pi^j_{mnt} = \frac{(d^j_{mnt} c_{mjt})^{1-\sigma}}{\sum_{m'=1}^{N} (d^j_{m'n} c_{m'jt})^{1-\sigma} + (d^j_{Fn} P^F_{jt})^{1-\sigma}} \quad \text{and} \quad \pi^j_{Fnt} = \frac{(d^j_{Fn} P^F_{jt})^{1-\sigma}}{\sum_{m=1}^{N} (d^j_{mn} c_{mjt})^{1-\sigma} + (d^j_{Fn} P^F_{jt})^{1-\sigma}}. \tag{4.5}$$

Total sector j export values of region n are

$$\mathrm{EX}_{njt} = (d^j_{nF} c_{njt})^{1-\sigma} D^F_{jt}. \tag{4.6}$$

D^F_{jt} is Foreign market demand exogenous to Home.

4.1.3 Household

Preference Households' preferences are Cobb-Douglas with expenditure shares α_j:

$$U(C_{nt}) = \ln C_{nt}, \qquad C_{nt} = \prod_{j=1}^{J} (C_{njt})^{\alpha_j}, \qquad \sum_{j=1}^{J} \alpha_j = 1.$$

C_{nt} is consumption. The ideal price index is $P_{nt} = \prod_{j=1}^{J} (P_{njt}/\alpha_j)^{\alpha_j}$. The budget constraint is $P_{nt} C_{nt} = I_{nt}$, where I_{nt} is total income earned by households

Sectoral labor supply Each household contains a continuum of workers with measure one indexed by h, $h \in [0, 1]$. Each worker has different amounts of labor efficiency units across sectors. Sectoral labor supply is determined by households' optimal allocation of their workers across sectors within regions, based on region-sector wages and workers' labor efficiency units. The total labor income earned by each household is the sum of wages earned by their workers. Each worker is ex-ante identical, but ex-post heterogeneous due to different ability draws across sectors. Workers receive new draws every period after households make migration decisions. Each worker is characterized by ability vector $\boldsymbol{\epsilon}^h_t = (\epsilon^h_{n1t}, \ldots, \epsilon^h_{nJt})$, where ϵ^h_{njt} is amounts of efficiency units of labor of member h that can be supplied to sector j.

Labor efficiency units of each worker are independently and identically drawn from a multivariate Fréchet distribution across regions and periods: $F_{nt}(\boldsymbol{\epsilon}_t) = \exp(-\sum_{j=1}^{J} E_{njt} \epsilon^{-\theta}_{njt})$ with $\theta > 1$ (Eaton and Kortum, 2002; Lagakos and Waugh, 2016; Hsieh et al., 2019). E_{njt} is the location parameter that varies at the region-sector-time level. E_{njt} can be interpreted as time-varying region-sector labor supply shocks, with the higher value of E_{njt} corresponding to a higher probability of drawing larger labor efficient units. θ is the shape parameter of the Fréchet distribution that governs the dispersion of skills across workers, with the higher value of θ corresponding to smaller dispersion.

Households allocate their available workers across sectors to maximize the total sum of wages earned by their workers. Households allocate worker h to sector j only if sector j generates the highest labor income over other sectors: $\epsilon^h_{njt} \in \Omega_{njt}$, where $\Omega_{njt} = \{\boldsymbol{\epsilon}_t | W_{njt}\epsilon_{njt} \geq W_{nkt}\epsilon_{nkt}, \forall k \in \mathcal{J}\}$. Shares of workers allocated to sector j are expressed as

$$\lambda_{njt} = \int_0^1 \left[\int_{\Omega_{njt}} dF_{njt}(\boldsymbol{\epsilon}^h_t) \right] \mathrm{d}h = \frac{E_{njt} W^\theta_{njt}}{\sum_{j'=1}^J E_{nj't} W^\theta_{nj't}}, \tag{4.7}$$

which is equal to the share of workers whose earnings are the highest in sector j. The labor supply of sector j in the unit of effective labor in region n is expressed as follows:[14]

$$H_{njt} = L_{nt} \int_0^1 \left[\int_{\Omega_{njt}} \epsilon^h_{njt} dF(\boldsymbol{\epsilon}^h_t) \right] \mathrm{d}h = \Gamma^1 \lambda_{njt}^{\frac{\theta-1}{\theta}} L_{nt}.$$

Labor supply curves are upward-sloping and increase in W_{njt}. The total labor income of region n's household is the sum of wages of their workers:

$$W_{nt} = \int_0^1 \max_{j \in \mathcal{J}} \{W_{njt}\epsilon^h_{njt}\} \mathrm{d}h = \Gamma^1 \Big(\sum_{j=1}^J E_{njt} W^\theta_{njt} \Big)^{\frac{1}{\theta}}. \tag{4.8}$$

Migration At the end of each period, households can migrate to another region where they work in the next period after they earn labor income and make consumption decisions in the current region. Households choose a region that gives the highest utility net of migration frictions. The dynamic problem of a household is

$$\mathrm{v}_{nt} = \ln C_{nt} + \max_{m \in \mathcal{N}} \left\{ \beta \mathbb{E}[\mathrm{v}_{m,t+1}] - \tau_{nmt} + \eta_{mt} \right\},$$

where v_{nt} is the lifetime utility of a household in region n and $\mathbb{E}[\mathrm{v}_{m,t+1}]$ is the future lifetime utility where the expectation is taken over the realization of all future shocks. Migration frictions are non-monetary costs, measured in terms of utility. These costs are origin-destination specific and can be time-varying, represented by the bilateral cost matrix τ_{nmt}.

They have idiosyncratic preference shocks over regions η_{nt} for each location, independently and identically distributed across households, regions, and time. η_{mt} is distributed Type-1 Extreme Value with zero means with the parameter ν.[15] Let $V_{nt} = \mathbb{E}_\eta[\mathrm{v}_{nt}]$, where the expectation is taken over the preference shocks, which is the lifetime expected utility before realization of the preference shocks. Under the distributional assumption, V_{nt} can expressed as:

$$V_{nt} = \ln C_{nt} + \nu \ln \sum_{m=1}^N \exp(\beta V_{m,t+1} - \tau_{nmt})^{\frac{1}{\nu}}. \tag{4.9}$$

[14] Γ^1 is a constant defined as $\Gamma^1 = \Gamma(1 - \frac{1}{\theta})$ where $\Gamma(\cdot)$ is the Gamma function.
[15] η_{mt} follows the Gumbel distribution with parameters, $(-\gamma\nu, \nu)$, where γ is Euler's constant.

Eq. (4.9) implies that the value of being in region n is the sum of the current utility and the option value of moving into other regions.

The fraction of households who migrate from region n to m at the end of period t admits the following closed form:

$$\mu_{nmt} = \frac{\exp(V_{m,t+1} - \tau_{nmt})}{\sum_{m'=1}^{N} \exp(V_{m',t+1} - \tau_{nm't})}. \tag{4.10}$$

The previous expression indicates that, all things being equal, households migrate more into regions with higher expected lifetime utility net of migration frictions, with the migration elasticity $1/\nu$. The migration elasticity governs how sensitive migration flows are to changes in expected lifetime utilities and migration frictions, with the lower value corresponding to more persistent location choices. Population is a state variable and evolves as

$$L_{n,t+1} = \sum_{m=1}^{N} \mu_{mnt} L_{mt}. \tag{4.11}$$

I allow for trade imbalances by incorporating exogenous trade deficits and introducing an exogenous tax common across households ι_t.[16] ι_t makes the ratio of per capita expenditure to per capita income vary exogenously over time:

$$\iota_t = \frac{\sum_{n=1}^{N} \sum_{j=1}^{J} (\mathrm{IM}_{njt} - \mathrm{EX}_{njt})}{\sum_{n=1}^{N} W_{nt} L_{nt}},$$

where IM_{njt} is sector j import values of region n. With exogenous trade deficits, households' income is given as $I_{nt} = (1 + \iota_t) W_{nt}$.

4.2 General Equilibrium

Market clearing Goods market clearing requires that

$$\mathrm{GO}_{njt} = \sum_{m=1}^{N} \pi_{mnt}^{j} \left[\Big(\sum_{k=1}^{J} \gamma_k^j \mathrm{GO}_{mkt} \Big) + \alpha_j (1 + \iota_t) W_{mt} L_{mt} \right] + \mathrm{EX}_{njt}, \tag{4.12}$$

where GO_{njt} is sector j gross output in region n. The term inside the brackets is region m's total expenditures on sector j goods. The labor market clearing condition is

$$W_{njt} H_{njt} = \gamma_j^H \mathrm{GO}_{njt}. \tag{4.13}$$

Shocks There are six time-varying exogenous shocks to the fundamentals, $\mathbf{\Psi}_t = \{A_{njt},\ E_{njt},\ P_{jt}^F,\ D_{jt}^F,\ \iota_t,\ \}_{n=1,j=1}^{N,J}$, and shocks to migration frictions, $\boldsymbol{\tau}_t = \{\tau_{nmt}\}_{n,m=1}^{N}$. Shocks in one region-sector

[16] If region-sector trade data are available, I can allow for heterogeneous trade imbalances at the regional level as in Caliendo et al. (2018).

transmit to other region-sectors through inter-regional trade and migration linkages.

Equilibrium Given the state variable $\{L_{nt}\}_{n=1}^{N}$ and $\mathbf{\Psi}_t$, allocation in each period is determined as in a static trade and spatial model. The population evolves according to the optimal migration decisions of households. I formally define the equilibrium as follows:

Definition 1. *Given the parameters of the model, $\{\mathbf{\Psi}_t\}_{t=t_0}^{\infty}$, $\{\boldsymbol{\tau}_t\}_{t=t_0}^{\infty}$, and initial allocations of the state variables $\{L_{nt_0}\}_{n=1}^{N}$, the competitive equilibrium of the model is the set of population, sectoral allocation of workers, wages, and expected lifetime utilities $\{L_{nt},\ \lambda_{njt},\ W_{njt},\ V_{nt}\}_{n=1,j=1,t=t_0}^{N,J,\infty}$ that satisfies the following condition for each region n, each region-sector nj and period t: (i) Given $\{W_{njt}\}_{n=1,j=1}^{N,J}$, households optimally allocate their workers across different sectors (eq., 4.7); (ii) $\{V_{nt}\}_{n=1}^{N}$ satisfies eq. (4.9); (iii) $\{L_{nt}\}_{n=1}^{N}$ evolves according to eq. (4.11); and (iv) goods and labor market clearing conditions are satisfied (eq., 4.12, 4.13).*

4.3 Real GDP and Welfare

Real GDP I first define sectoral PPIs using each region's gross output shares within sectors as a Tornqvist index[17]:

$$\widehat{\mathrm{PPI}}_{jt} = \sum_{n=1}^{N} \omega_{njt}^{\mathrm{PPI}} \hat{P}_{njt}, \qquad \omega_{njt}^{\mathrm{PPI}} = \frac{1}{2}\left(\frac{\mathrm{GO}_{nj,t-1}}{\sum_{n=1}^{N}\mathrm{GO}_{nj,t-1}} + \frac{\mathrm{GO}_{njt}}{\sum_{n=1}^{N}\mathrm{GO}_{njt}}\right). \tag{4.14}$$

The hat denotes time differences for any variable x: $\hat{x}_{t+1} = x_{t+1}/x_t$. $\tilde{\omega}_{njt}^{\mathrm{PPI}}$ is the average of region n's shares of sector j gross output in periods $t-1$ and t.

Using these sectoral PPIs, I define aggregate real GDP:

$$\hat{Y}_t^r = \sum_{n=1,j=1}^{N,J} \omega_{njt}^{\mathrm{agg},r} \widehat{\mathrm{VA}}_{njt}^{r}, \quad \widehat{\mathrm{VA}}_{njt}^{r} = \frac{\widehat{\mathrm{VA}}_{njt}}{\widehat{\mathrm{PPI}}_{jt}}, \quad \omega_{njt}^{\mathrm{agg},r} = \frac{1}{2}\left(\frac{\mathrm{VA}_{nj,t-1}}{\sum_{n=1,j=1}^{N,J}\mathrm{VA}_{nj,t-1}} + \frac{\mathrm{VA}_{njt}}{\sum_{n=1,j=1}^{N,J}\mathrm{VA}_{njt}}\right). \tag{4.15}$$

VA_{njt} is region-sector nj's nominal value-added: $\mathrm{VA}_{njt} = \gamma_j^H \mathrm{GO}_{njt}$. $\widehat{\mathrm{VA}}_{njt}^{r}$ is region-sector nj's real value-added growth deflated by the sectoral PPI. Given that real GDP is a measure for real value-added, I use the value-added shares for aggregation following Caliendo et al. (2021). Similarly, I define regional real GDP using the regional weights:

$$Y_{nt}^r = \sum_{j=1}^{J} \omega_{njt}^{reg,r} \widehat{\mathrm{VA}}_{njt}^{r}, \qquad \omega_{njt}^{\mathrm{reg},r} = \frac{1}{2}\left(\frac{\mathrm{VA}_{nj,t-1}}{\sum_{j=1}^{J}\mathrm{VA}_{nj,t-1}} + \frac{\mathrm{VA}_{njt}}{\sum_{j=1}^{J}\mathrm{VA}_{njt}}\right). \tag{4.16}$$

[17] di Giovanni et al. (2020) and Choi et al. (2023) define sectoral PPIs similarly.

Welfare The expected lifetime utility of households living in region n in t can be expressed as

$$V_{nt} = \sum_{s=t}^{\infty} \beta^{s-t} \ln\left(\frac{C_{ns}}{\mu_{nns}^{\nu}}\right).$$

4.4 Taking Stock

Crisis and shocks I model the crisis as five time-varying exogenous shocks in a reduced-form fashion, $\mathbf{\Psi}_t^{\text{crisis}} = \{A_{njt}, E_{njt}, D_{jt}^F, P_{jt}^F, \iota_t\} \subset \mathbf{\Psi}_t$, capturing key features of emerging market economies after crises.

Lower A_{njt} represents large drops in TFP and real GDP (e.g., Meza and Quintin, 2007; Pratap and Urrutia, 2012; Queralto, 2020). A_{njt} can be related to not only physical productivity but also negative financial shocks. I illustrate this by developing a simple model as in Kim et al. (2015), in which the balance sheet effects show up as A_{njt} under working capital constrains (Appendix Section C.2). E_{njt} can be related to labor market frictions, such as unemployment due to downward nominal rigidity.[18] I extend the model to incorporate unemployment rate due to downward nominal rigidities as in Rodriguez-Clare et al. (2022), and show that employment rate appears in a position of E_{njt} in eq. (4.7) in Appendix Section E.1.[19]

Higher D_{jt}^F and P_{jt}^F explain large export expansions and import collapses due to devaluations in the crisis, respectively. Alessandria et al. (2010), Gopinath and Neiman (2014), Blaum (2018) and Blaum et al. (2018) similarly model devaluations as exogenous shocks to foreign demand and import costs. Finally, ι_t captures a rapid decline in trade deficits after crises (e.g., Kehoe and Ruhl, 2009; Mendoza, 2010). Given that the focus of this paper is adjustment to large crises rather than explaining factors behind changes in trade deficits, I treat trade deficits as exogenous as is standard in the trade literature (Dekle et al., 2008).[20]

Spatial misallocation and labor reallocation Because of the sudden shocks, reallocating labor across regions through migration has the potential to increase total output. In response to the shocks, labor is reallocated across region-sectors based on households' sectoral labor supply and migration decisions. The total amounts of workers working in region-sector nj are

$$L_{njt} = \underbrace{\lambda_{njt}}_{\substack{\theta\,:\,\text{Sectoral reallocation} \\ \text{within regions}}} \times \underbrace{\mu_{nm,t-1} L_{m,t-1}}_{\substack{1/\nu\,:\,\text{Spatial reallocation} \\ \text{across regions}}}.$$

[18] Schmitt-Grohé and Uribe (2016) show that under downward nominal rigidity, currency pegs can be costly for welfare and employment. Drenik (2016) and Blanco et al. (2022a) document heterogeneous degree of downward nominal rigidities across sectors due to union. They show that this heterogeneity is important in understanding distributional effects of large devaluations.

[19] An alternative way to allow for unemployment in quantitative trade models is introducing matching frictions as in Carrère et al. (2020) and Kim and Vogel (2021).

[20] See Reyes-Heroles (2016) and Dix-Carneiro et al. (2021) for incorporating endogenous trade imbalances in the quantitative trade frameworks.

Both θ and $1/\nu$ govern two conceptually distinct decisions of workers on which sector to work in (sectoral labor supply) and where to live (migration), respectively.[21] $1/\nu$ governs the evolution of population through migration flows. θ governs changes in employment shares within regions conditional on population.

Model extension I show that the model can be extended to several dimensions. First, I show that the model can be extended to feature unemployment due to downward nominal rigidity (Rodriguez-Clare et al., 2022). Second, the model can be extended to incorporate intertemporal investment in capital as in Kleinman et al. (2021).

4.5 Counterfactual

To perform counterfactuals, I use a dynamic hat algebra developed by Caliendo et al. (2019), solving the model in changes. This approach requires information on the initial allocation in 1997, the structural parameters, the shocks in changes

$$\{\hat{\boldsymbol{\Psi}}_t\}_{t=98}^{\infty} = \{\hat{A}_{njt}, \hat{E}_{njt}, \hat{D}_{jt}^F, \hat{P}_{jt}^F, \iota_t\}_{t=98}^{\infty},$$

and counterfactual migration frictions shocks $\{\hat{m}_{mnt}\}_{t=97}^{\infty}$, where $\hat{m}_{mnt} = \exp(\tau_{mnt} - \tau_{mn,t-1})$. I conduct two main exercises: the first examines the relationships between mobility levels and transitional dynamics, while the second examines the welfare effects of the crisis.

Migration mobility and transitional dynamics In the first exercise, I analyze how the economy would have adjusted differently to the same shocks with varying levels of migration mobility. I construct counterfactual economies with different mobility levels by jointly feeding the exogenous shocks and the migration friction shocks into the initial allocation. For the baseline economy, I assume there are no changes in migration frictions ($\hat{m}_{mnt} = 1$, $\forall t$) and only feed in the exogenous shocks.

I mainly consider temporary changes in migration friction shocks that last up to 3 years, returning to the original levels 4 years after the crisis. These changes could result from potential migration policies, such as the temporary promotion of rural workers migrating to urban regions (see Lagakos et al., 2023), implemented during the crisis. These temporary changes may reflect more realistic policy options compared to permanent changes, as permanent changes are typically more costly. One year before the crisis in 1997, these unexpected and transitory migration friction shocks occur, influencing households' migration decisions before the anticipated crisis in 1998. The friction levels

[21] Alternatively, I can model workers to make migration decisions from one region-sector to other region-sectors similar to Caliendo et al. (2019). Such modeling requires data on transitions between region-sectors and frictions of reallocating across different sectors can be inferred from the observed sector-to-sector transition flows combined with the model. However, because of unavailability of sector-to-sector transition flows in my setting, I made workers have two decisions that are governed by the two distinct elasticities, whereas in the model of Caliendo et al. (2019), workers' decisions are governed by a single elasticity. Recently, Rodriguez-Clare et al. (2022) introduced separate elasticities for these two decisions by using a nested structure of households' labor supply decisions.

remain constant between 1998 and 2001 and then revert to their original levels in 2002. Specifically, I introduce the shock $\hat{m}_{mn,97}$ in 1997. $\hat{m}_{nmt} = 1$ for $t \in \{98, 99, 00, 01\}$. $\hat{m}^c_{nm,02} = 1/\hat{m}^c_{nm,97}$.

I consider four counterfactual mobility levels. The first and the second are no- and full-mobility, which can be approximated as $\hat{m}_{nm,97} = C$, $\forall n, m \in \mathcal{N}$ for some large and small numbers, respectively.[22] The free-mobility resembles a setting of the canonical tradable-nontradable models without any reallocation costs in international macro literature (e.g. Uribe and Schmitt-Grohé, 2017). In the third, there are common reductions of 10% in migration frictions for all pairs: $\hat{m}_{nm} = 0.90$, $\forall n, m \in \mathcal{N}$. The number of 10% is obtained from frictions inferred from the observed migration shares (Head and Ries, 2001).[23] Between 1997 and 2007, at the median, there were 10% reductions among the inferred frictions.[24] Following Monte et al. (2018), I use this number to conduct counterfactuals for empirically-plausible levels of reductions. In the last, directional reductions of 10% are applied only for migration flows to regions with higher top 5 employment shares: $\hat{m}_{nm,97} = 0.90$ for regions n and m that satisfy $\text{Empsh}^{\text{top5}}_{m,94} > \text{Empsh}^{\text{top5}}_{n,94}$. This reflects policy outcomes where the government deliberately promotes migration to regions with a higher concentration of employment in the top 5 sectors to strategically influence sectoral reallocation during the crisis.

Welfare In the second exercise, I assess the welfare effects of the crisis by comparing the baseline to the no-crisis counterfactual under different mobility levels. To compute the welfare effects at different mobility levels, I feed the counterfactual migration frictions in the baseline and the no-crisis counterfactual which constructed by turning off the crisis shocks ($\hat{\boldsymbol{\Psi}}^{crisis}_t = 1$). For each mobility level, I compute welfare changes measured in terms of consumption equivalent variation:

$$\triangle V_{n,97} = \sum_{s=1997}^{\infty} \beta^{s-1997} \ln \frac{(C^c_{ns}/C^b_{ns}}{(\mu^c_{nns}/\mu^b_{nns})^{\nu}},$$

where the superscripts b and c denote variables of the baseline and counterfactual, respectively.[25] It is worth noting that because the same migration frictions are fed in, the welfare effects of migration frictions per se are absorbed out by dividing them. Therefore, I focus on how welfare changes vary depending on mobility levels. The aggregate welfare changes are computed, following the Utilitarian approach, as the weighted average of regional welfare changes, with weights given by the initial population, following Caliendo et al. (2019): $\triangle V^{\text{agg}}_{97} = \sum_{n=1}^{N} \frac{L_{n,97}}{\sum_{m=1}^{N} L_{m,97}} \triangle V_{n,97}$.

[22] Computationally, I set $C = 10,000$ and $C = 0.01$ for the no- and full-mobility, respectively.

[23] Under the symmetry ($\tau_{mnt} = \tau_{nmt}$, $\forall n, m \in \mathcal{N}$), migration frictions can be inferred from the observed migration shares: $\mathfrak{m}_{nmt} = \exp(\tau_{nmt})^{\frac{1}{\nu}} = (\frac{\mu_{nmt}\mu_{mnt}}{\mu_{nnt}\mu_{mmt}})^{-0.5}$, where $\mathfrak{m}_{nmt}$ captures the ease of migration. As in Bryan and Morten (2019), I show that the inferred frictions are highly correlated with observed proxies for migration frictions, such as distance and an index for regional conflicts (Appendix Section D.5).

[24] Monte et al. (2018) also find 12% reductions in commuting frictions between 1990 and 2010, the similar magnitude of the 10%. Improvement of transportation infrastructure can be one factor behind the 10%. Between these periods, kilometers of paved public roads increased by 32% (from 82,000 to 109,000), and those of highways increased by 235% (from 1,900 to 4,400).

[25] See Appendix Section C.1 for detailed derivation of the welfare formula.

Table 4: Summary of Calibration

Parameters	Value	Description	Target
Elasticities			
$1/\nu$	0.7	Migration elasticity	IV estimates, eq. (4.17)
θ	1.5	Sectoral labor supply elasticity	Galle et al. (2022)
σ	6	Trade elasticity	Costinot and Rodríguez-Clare (2014)
Geographic frictions			
$\{\xi_j\}$	0.26, 0.4	Trade costs	Monte et al. (2018), Eckert (2019)
Shocks			
$\{\hat{A}_{njt}\}$		Productivity shocks	Gross output, PPI
$\{\hat{E}_{njt}\}$		Labor productivity shocks	Region-sector emp. shares
$\{\hat{D}^F_{jt}\}$		Foreign demand shocks	Aggregate exports
$\{\hat{P}^F_{jt}\}$		Import price shocks	Aggregate imports
$\{\iota_t\}$		Trade deficits	Aggregate exports/imports
Preference			
β	0.96	Discount factor	Literature
$\{\alpha_j\}$		Final consumption shares	IO table
Production			
$\{\gamma_j^H, \gamma_j^k\}$		IO coefficients, value-added shares	IO table

Notes. This table summarizes the calibration results.

4.6 Taking the Model to the Data

This section discusses the calibration procedure for the structural parameters, the initial allocation, the exogenous shocks to the fundamentals, and the counterfactual migration friction shocks. Table 4 reports a summary of the calibration procedure. See Appendix Section D for more details.

4.6.1 Structural Parameters

Discount factor I set the one-year discount factor β to the conventional value 0.96.

Migration elasticity I can derive an estimable specification from the model and estimate it in first-differences between 1997 and 2000 to recover migration elasticity $1/\nu$ (Artuc et al., 2010)[26]:

$$\triangle \ln \frac{\mu_{nmt}}{\mu_{nnt}} = \frac{\beta}{\nu} \triangle \ln \frac{I_{m,t+1}/P_{m,t+1}}{I_{n,t+1}/P_{n,t+1}} + \beta \triangle \ln \frac{\mu_{nm,t+1}}{\mu_{mm,t+1}} + \mathbf{X}'_{nmt_0}\gamma + \tilde{\epsilon}_{nmt}. \tag{4.17}$$

[26]The expression captures that current migration flows reflect the future values of expected real income and the option values, where the future migration flows are the sufficient statistics for the option values. Conditioning on the option values, variation in real income differences across regions identifies the migration elasticity. See Appendix Section D.1 for more details on the derivation of the regression model from the theoretical framework.

Any time-invariant components of migration costs or differences in amenities between two regions. $\tilde{\epsilon}_{nmt}$ is the structural error term that is a function of differenced migration friction shocks. Depending on specifications, I control for observables $\mathbf{X}_{nmt_0}$ similar to eq. (3.1), including the initial log employment, the pretrends of migration flows, the regional exposures to balance sheet effects, and the initial log unemployment rate and the initial amenity index.

To run the above regression, I need data on I_{nt} and P_{nt}. I compute I_{nt} by dividing region n's total value-added in region n, multiplied by observed $(1 + \iota_t)$ that rationalizes trade deficits, by its employment. Regional price levels P_{nt} are obtained from the regional consumer price Index (CPI) data.[27] The Korean statistical agency only reports CPI data of the selected regions. Therefore, following Moretti (2017), I impute CPI data for regions with missing information using housing price data that are available for all regions. Out of 54 regions, the regional CPI data is available for 32 regions and CPIs of the remaining 22 regions are imputed. See Appendix Section D.1 for more detail.

Because differences in real income can be correlated with amenities or migration frictions shocks, the OLS estimates may suffer from the endogeneity problem. Therefore, I estimate eq. (4.17) using the following IV:

$$\mathrm{IV}_{nmt} = (\mathrm{Empsh}^{\mathrm{top5}}_{m,94} - \mathrm{Empsh}^{\mathrm{top5}}_{n,94}). \tag{4.18}$$

The identifying assumption of the IV holds when migration friction shocks are uncorrelated with the initial differences in the top 5 employment shares, reflecting differential local labor market shocks after the crisis, conditional on the fixed effects and controls.

The IV estimate is statistically significant at the 5% level (Table 5). With the assumed value of the discount factor, this estimate gives a value of $1/\nu$ around 0.8. The estimates are stable with the additional controls and the exclusion of the pairs within 100km (col. 3-5). The first-stage is strong, with Kleibergen-Paap F-statistics (KP-F around 18), above the rule of thumb value 10. I can also reject the null hypothesis of weak instrument using the test proposed by Montiel Olea and Pflueger (2013).[28] The estimates are also significant at the 5% level based on the Anderson-Rubin (AR) statistics which is robust to weak instruments.[29]

The estimates are in line with the estimates from the previous papers. Caliendo et al. (2021) report

[27] One concern with using the CPI is that it is comparable across times within regions but not cross-sectionally across regions, because the CPI is normalized to be one in the base year. However, controlling for δ_{nm} makes the cross-sectional comparisons available by absorbing out differences in unobservable price levels of the base year under the log utility function.

[28] Montiel Olea and Pflueger (2013) propose a conservative test accommodating heteroskedasticity, serial correlation, and clustering. When there is a single instrument as in the current setup, the KP-F is equivalent to their effective F-statistics. The KP-F values exceeds the critical cutoff of 15.1, which corresponds to a test for IV relative bias of no more than 20% at a 5% significance level.

[29] Inference based on the AR statistics is robust to weak instruments in the sense that their probability of incorrectly rejecting the null hypothesis and covering the true parameter value remains well-controlled. Because the IV estimates are non-normally distributed with weak instruments, the AR statistics use test inversion rather than rely on point estimates and standard errors (Andrews et al., 2019).

Table 5: Estimates of the Migration Elasticity

Sample	Full sample			Dist. $\geq$ 100km	
	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
	Panel A. Second Stage				
$\triangle \ln \frac{I_{m,t+1}/P_{m,t+1}}{I_{n,t+1}/P_{n,t+1}}$	-0.00	0.80**	0.75**	0.88**	0.81**
	(0.11)	(0.34)	(0.34)	(0.36)	(0.34)
KP-F		17.66	18.50	16.79	18.86
AR $\{p$-val.$\}$		5.62 {0.02}	5.06 {0.02}	6.69 {0.01}	6.19 {0.01}
AR-CI, 95%		$[0.19, 2.04]$	$[0.12, 1.90]$	$[0.26, \infty]$	$[0.21, 1.99]$
	Panel B. First Stage				
IV_{nmt}		0.21***	0.21***	0.20***	0.22***
		(0.05)	(0.05)	(0.05)	(0.05)
Control			✓		✓
Pair FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
# Cluster (Origin)	54	54	54	54	54
# Cluster (Dest.)	54	54	54	54	54
N	2914	2914	2914	2914	2082

Notes. Standard errors two-way clustered at the origin and destination levels are in parenthesis. *: p<0.1; **: p<0.05; ***: p<0.01. This table reports the OLS and IV estimates of eq. (4.17). Panels A and B report the second and the first stage results, respectively. Column 1 reports the OLS estimate. Columns 2 and 3 report the IV estimates, where the IV is defined in eq. (4.18). In columns 3, I control for differences in the initial industrial composition (eq (3.4)) interacted with the post-crisis dummy and the origin and destination's initial amenity interacted with the post-crisis dummy. All specifications include pair and year fixed effects. KP-F is the Kleibergen-Paap F-statistics.

a value of 0.5 at the annual frequency, and Caliendo et al. (2019) report one of 0.2 at the quarterly frequency. The higher estimate in this study may be attributed to the more granular geographic size of the spatial units compared to those in the two papers.

Other elasticities I calibrate $\theta = 1.5$ based on the estimates from the recent literature.[30] I set the trade elasticity to $\sigma - 1 = 4$ (Costinot and Rodríguez-Clare, 2014).

Trade costs I parametrize internal trade costs as a function of physical distance: $d^j_{nm} = (\text{Dist}_{nm})^{\xi_j}$ where Dist_{nm} is distance between regions and ξ_j are parameters that potentially vary across sectors.

[30] Burstein et al. (2019) report values of 1.26–1.81; Hsieh et al. (2019), 1.5–2.6; Lee (2020), 1.05–1.47; and Galle et al. (2022), 2.

I set $(\sigma - 1)\xi_j$ to be 1.29 for commodity and manufacturing sectors and 2 for service sectors based on the estimates from Monte et al. (2018) and Eckert (2019). I parametrize international trade costs as $d^j_{Fn} = (\text{PDist}_n)^{\xi_j}$, where PDist_n is the minimum distance to port of region n. International trade costs that are common across regions are not separately identifiable from P^F_{jt} and D^F_{jt}, so d^j_{Fn} capture the costs relative to those of regions with ports.

IO coefficients and final consumption shares I obtain value-added shares, IO coefficients, and final consumption good shares from the WIOD.

4.6.2 Initial Allocation

I need the initial allocation of $\{\text{GO}_{njt_0}, \lambda_{njt_0}, \mu_{nm.t_0-1}, L_{nt_0}, \text{EX}_{njt_0}, \pi^j_{nmt_0}, \pi^j_{Fnt_0}\}^{N,J}_{n,m=1,j=1}$ to apply the dynamic hat algebra. I obtain $\{\text{GO}_{njt_0}, \lambda_{njt_0}, L_{nt_0}, \mu_{nm,t_0-1}\}^{N,J}_{n,m=1,j=1}$ from the data. However, I do not have information on $\{\text{EX}_{njt_0}, \pi^j_{Fnt_0}, \pi^j_{nmt_0}\}^{N,J}_{n,m=1,j=1}$. I indirectly infer these variables from sectoral exports and imports, region-sector gross output, and the gravity structure of trade under the parametrized trade costs. Under the gravity structure, there exists a unique set of trade shares that rationalize observed region-sector gross output and sectoral exports and imports (Allen et al., 2020). Thus, I can infer these variables by solving the gravity structure given the available data.[31] See Appendix 4.6 for this procedure.

4.6.3 Recovering Shocks

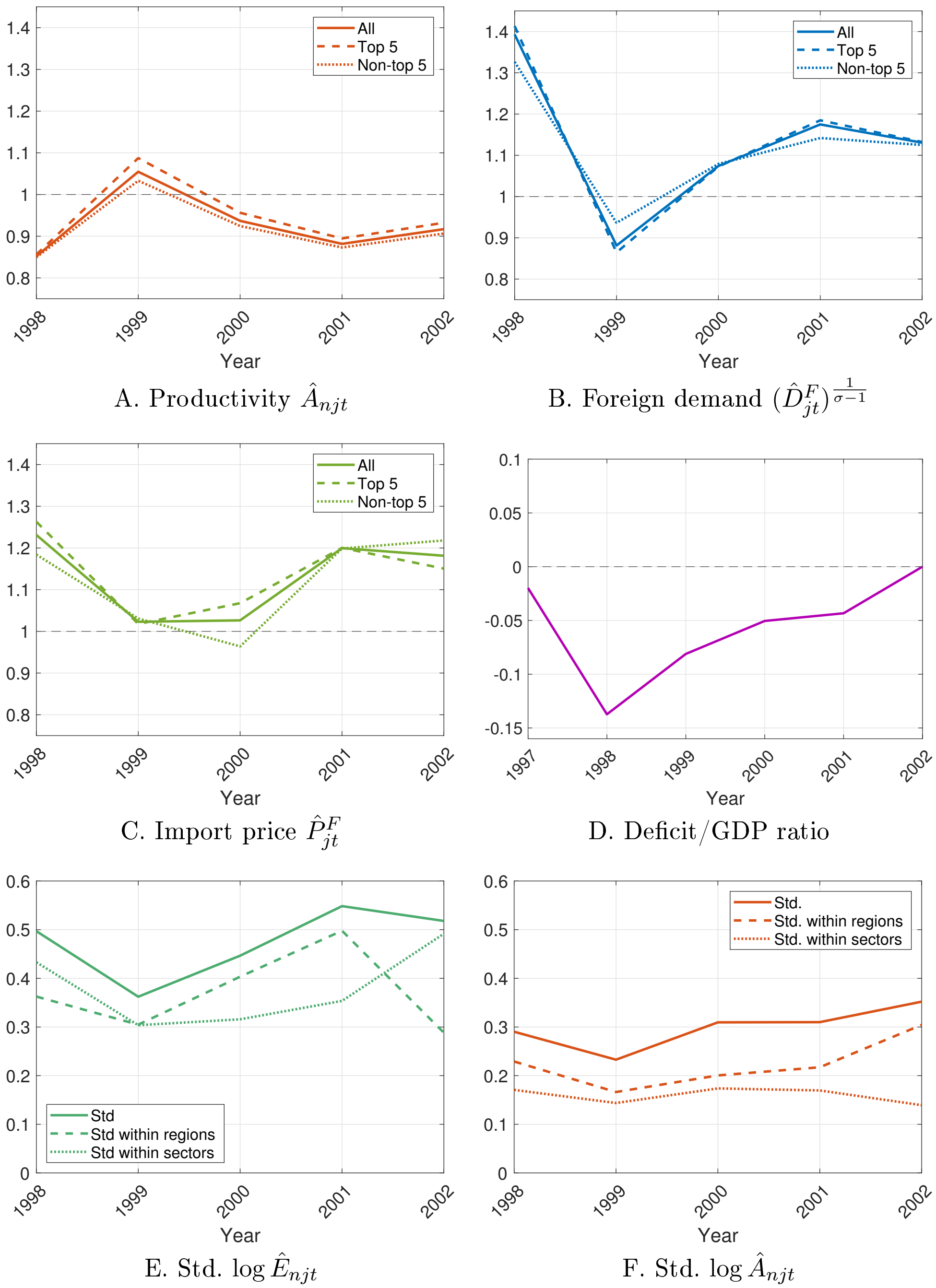
I assume that the model reaches the steady state for a sufficiently large period $T = 2072$. After 2002, I set the shocks $\hat{\boldsymbol{\Psi}}_t$ to start converging to their 1997 original level in 2003 and reach the original level 30 years after the crisis. More specifically, given the values of $\{\hat{\boldsymbol{\Psi}}_t\}^{02}_{t=98}$, after 2002, the shocks evolve as

$$\hat{\boldsymbol{\Psi}}_t = 1/\Big(\prod_{\tau=98}^{02} \hat{\boldsymbol{\Psi}}_\tau\Big)^{\frac{1}{25}}, \quad \forall t \in \{03, \ldots, 28\} \quad \text{and} \quad \hat{\boldsymbol{\Psi}}_t = 1, \quad \forall t \in \{29, \ldots, T\}.$$

Under the assumed shock process, I recover the shocks between 1997 and 2002 $\{\hat{\boldsymbol{\Psi}}_t\}^{02}_{t=98}$ by fitting the model to the data (e.g., Allen and Arkolakis, 2014; Eaton et al., 2016; Redding, 2016). I take into account the fact that agents have perfect foresight on the sequence of the shocks. The model is fitted to sectoral gross output distributions across regions, sectoral PPIs, aggregate real GDP growth, region-sector employment shares, sectoral import shares, exports, and regional population distribution between 1997 and 2002.[32] See Appendix Section D.4 for more details on the calibration procedure of the shocks.

[31] Similarly, Gervais and Jensen (2019) and Eckert (2019) indirectly infer trade flows using region-sector gross output (or value-added) and the gravity structure.

[32] I detrend sectoral PPIs and aggregate real GDP using the Hodrick-Prescott (HP) filter to isolate the cyclical component of the data from the trend components. I set the smoothing parameter to 100.



A. Productivity $\hat{A}_{njt}$

B. Foreign demand $(\hat{D}_{jt}^{F})^{\frac{1}{\sigma-1}}$

C. Import price $\hat{P}_{jt}^{F}$

D. Deficit/GDP ratio

E. Std. $\log \hat{E}_{njt}$

F. Std. $\log \hat{A}_{njt}$

Figure 4. Recovered Shocks

Notes. The figure presents the evolution of the shocks. Panels A, B, and C plot the weighted average of the productivity, foreign demand, and import price shocks, where the weights are given by region-sector gross output, sectoral imports, and sectoral exports, respectively. The solid, dashed, and the dotted lines represent all, the top 5, and the remaining sectors, respectively. Panel D plots the ratio of deficits to GDP in level. Panel D reports the deficit ratio to the GDP. Panels E and F plot standard deviations of log labor supply and productivity shocks across region-sectors, and the unweighted averages of within-region and -sector standard deviations.

Although all shocks are jointly identified, some data variables are more relevant to particular shocks. $\hat{A}_{njt}$ are mainly identified from gross output, PPIs, and aggregate real GDP growth. Regional distributions of gross output identify the relative $\hat{A}_{njt}$ of each region for each sector in a given year. PPIs and aggregate real GDP growth identify the absolute levels. Conditioning on the identified $\hat{A}_{njt}$, region-sector employment shares identify $\hat{E}_{njt}$; and aggregate import shares and exports identify $\hat{P}^F_{jt}$ and $\hat{D}^F_{jt}$, respectively.[33] Without E_{njt}, there is a one-to-one mapping between gross output and employment shares within regions, which is not the case in the data. Introducing E_{njt} allows the model to account for variation in both gross output and employment shares in the data. Finally, the exogenous trade deficits ι_t are directly taken from the data as standard in the trade literature.

Figure 4 illustrates the evolution of the recovered shocks. Panels A, B, and C present the weighted averages of productivity, foreign demand, and import cost shocks, with weights assigned based on region-sector gross output, sectoral imports, and sectoral exports, respectively. Panel D presents the deficits-to-GDP ratio. In the crisis year, productivity decreased by 11%, foreign demand increased by 21%, and the average import costs rose by 11% relative to the previous year. Also, the deficit ratio declined by 12 percentage points because of increased exports and a collapse in imports. The top 5 sectors exhibited larger rebounds in productivity growth in 1999 and larger foreign demand growth in 1998, compared to the otherscon.

In general, a larger magnitude of spatial misallocation is expected when shocks become more dispersed. I document the regional dispersion of labor supply and productivity shocks. Panel E presents standard deviation of log labor productivity across region-sectors and unweighted averages of within-region standard deviation across sectors and within-sector standard deviation across regions. Compared to the crisis year, overall dispersion of labor supply shocks decreased by 45% in 2002.[34] Similar patterns are observed for within-sector and within-region dispersions. The dispersion of labor supply shocks was not only higher than that of productivity but also experienced a larger decline during the recovery. The standard deviation of log productivity was 65% smaller in the crisis year and decreased by around 7% (Panel F). The large dispersion of labor supply shocks suggests that labor supply side could have been an important factor in driving the initial misallocation.

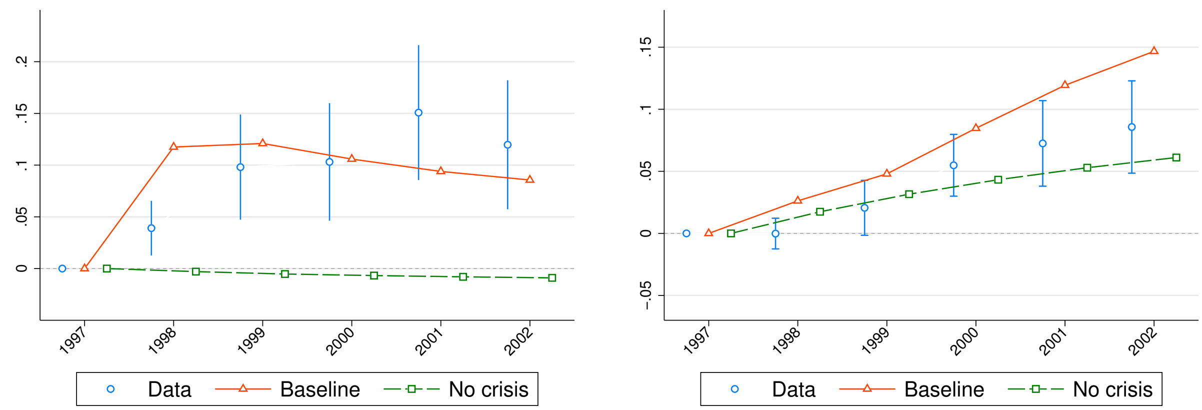
4.6.4 Non-Targeted Moments

I present the non-targeted moments of the model. The model is fitted to employment shares, population, and gross output, but not directly to migration flows or regional levels of employment. However, the model captures data moments on changes in migration flows and employment after the crisis. Using the model-generated data after 1997, I run the same event-study specifications with the same set of controls (eq., 3.5 and 3.7). Figure 5 reports the non-targeted moments. Most of the estimates

[33] Conditional on $\hat{A}_{njt}$, $\hat{E}_{njt}$ are identified upto normalization, so $\hat{E}_{njt}$ of the reference sector is set to 1 for all regions and periods.

[34] This aligns with Drenik (2016) who documents heterogeneous downward nominal rigidities across sectors, resulting in varying unemployment rates and, consequently, heterogeneous labor supply shocks. The observed regional dispersion may align with potential heterogeneous downward nominal rigidities across regions.

Figure 5. Non-Targeted Moments. Migration, Employment, and the Crisis



A. Migration outflow

B. Top 5 employment

Notes. This figure presents the non-targeted moments of the model. The blue circle represents the estimated event study coefficients from the data, with the 95% confidence intervals (Figures 2 and 3). The triangle and rectangular represent the estimated event study coefficients from the model generated data. In Panels A and B, the dependent variables are log migration shares and log top 5 employment, respectively.

from the model-generated data are within the 95% confidence intervals of the original estimates. When all exogenous shocks are deactivated, simulating a counterfactual scenario without the crisis, the model-generated data fails to replicate the estimates for migration inflows. However, for the top 5 employment both baseline and no-crisis estimates fall within the confidence interval, the baseline estimates within the upper range, while the no-crisis estimates within the lower range. Similar patterns are observed for other variables, including migration outflows, and total and non-top5 employment (Appendix Figure D12).

Additional non-targeted moments are population distributions. The population distribution from the model matches the actual distribution from the data well.

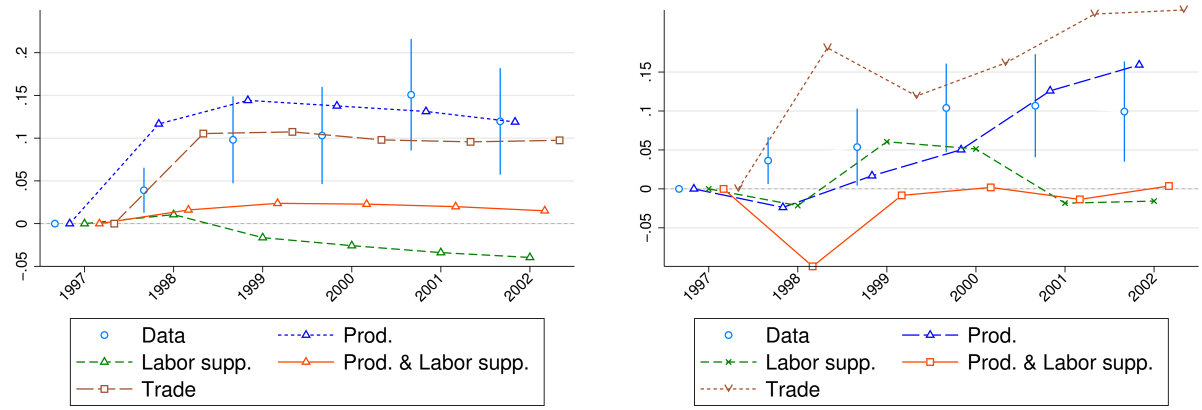
5 Quantitative Results

5.1 Migration, Employment, and the Role of Individual Shocks

I begin by investigating the role of individual shocks on migration and employment. I shut down a set of specified shocks at a time, keeping the remaining the same. Then, I run the event study specifications in eq. (3.1) and (3.7) using the model generated data. I shut down productivity ($\hat{A}_{njt}$), labor supply ($\hat{E}_{njt}$), and trade-related shocks ($\hat{D}^F_{jt}$, $\hat{P}^F_{jt}$, and ι_t).

Figure 6 reports the results. When I shut down labor supply shocks, the model cannot generate

Figure 6. The Role of Individual Shocks



A. Migration Inflow

B. Regional top 5 emp.

Notes. Panels A and B present the estimated event study coefficients when turning off a set of specified shocks at a time. The blue circle represents the estimated event study coefficients from the data, with the 95% confidence intervals (Figures 2 and 3).

increases in migration flows and employment (Panels A and B). The estimated coefficients without labor supply shocks remained flat, out of the 95% confidence intervals of the estimates from the data. Trade-related shocks had a more limited role. Related to top 5 employment, labor supply shock also played the largest role. Shutting down both labor supply and productivity shocks made the estimates from the model generated data out of the 95% confidence intervals. When feeding in specified shocks, labor supply shocks also played the largest role (Panels C and D). I obtain similar results for the other variables (Appendix Table D14). As robustness checks, I also consider feeding in a set of specified shocks at a time, while turning off the remaining shocks, reported in Appendix Figure D14. These results highlight the importance of labor supply shocks in understanding dynamics of migration flows and employment during the crisis.

In this exercise, I treated productivity or labor supply and trade-related shocks as orthogonal, that is, the two shocks remain the same when shutting down or feeding in trade-related shocks. However, trade shocks can be related to the other two, for example, as documented in Gopinath and Neiman (2014) and Blaum (2018) who show that higher import price shocks can decrease productivity through firm-level nonhomothetic import behaviors. In such case, trade shocks can have larger impacts by affecting the two shocks.

Table 6: Average Outflow Migration Rate, 1997–2002

	Baseline	No-mobility	Free-mobility	Decrease med. (common)	Decrease med. (undirectional)
	(1)	(2)	(3)	(4)	(5)
$\sum_m \mu_{nmt}$ (%)	9.50	0	92.9	10.94	10.34

Notes. The table reports the average outflow migration rates across regions between 1997 and 2002 of the baseline and counterfactual economies with different migration mobility levels.

Table 7: Sectoral Reallocation of Labor

	Baseline	No-mobility	Full-mobility	Decrease med. (common)	Decrease med. (undirectional)
	(1)	(2)	(3)	(4)	(5)
Aggregate employment shares in the top 5 sectors, $\text{Empsh}_t^{\text{top5}}$ (%)					
Avg. 1998–2002	18.59	18.06	19.77	18.65	18.82

Notes. The table reports the aggregate employment shares in the top 5 sectors in 2000 of the baseline and counterfactual economies with different migration mobility levels.

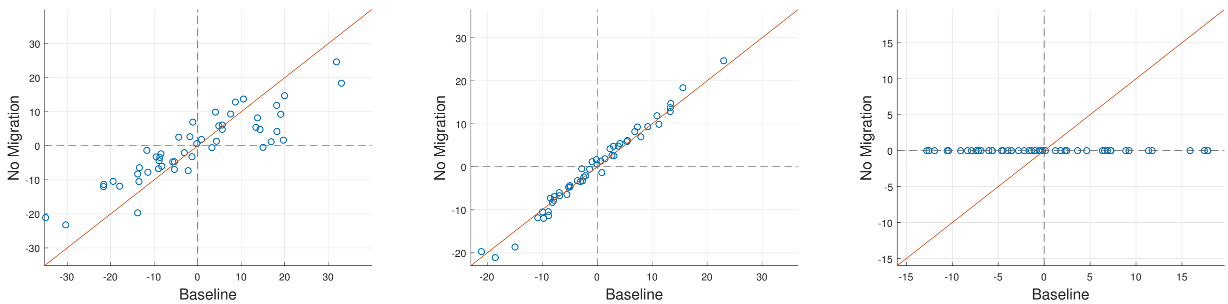
5.2 Counterfactual Analysis

5.2.1 Migration Mobility and Transitional Dynamics

I next quantitatively explore transitional dynamics under the baseline and the counterfactuals with different levels of mobility. Table 6 reports the average outflow migration rates between 1997 and 2002. In the baseline, the average rate was 9.8%, similar to the average of 11% in the data (Table 1). In the extreme full-mobility case, the average rate was 72.3%, implying that the baseline's mobility rates were closer to the no-mobility than the full-mobility.

Sectoral reallocation of labor and real GDP Because of the imperfect mobility of labor and the heterogeneous industrial composition across regions, desired amounts of sectoral reallocation may not be achieved after the crisis. I examine the relationships between the levels of mobility and the aggregate employment shares in the top 5 sectors. Table 7 reports the aggregate top 5 employment shares in 2000, with higher mobility being associated with larger top 5 shares. As shown in $L_{njt} = \lambda_{njt} L_{nt}$, the increase can come from changes in either employment shares within regions

Figure 7. Regional Effects. Baseline versus No-Mobility Counterfactual



Between 1997–2000

A. Changes, top 5 emp. (%) B. Changes, top 5 emp. shares (%) C. Changes, pop. (%)

Notes. Panels A, B, and C illustrate the changes in regional top 5 employment, top 5 employment shares, and population in 2000 relative to 1997 for both the baseline and the no-mobility counterfactual. Each dot represents a region, with the x- and y-axes corresponding to the baseline and the no-mobility counterfactual. The red line represents the 45-degree line.

λ_{njt} or population adjustment L_{nt} at the extensive margin. Most of the changes come from population adjustments. For example, Figure 7 compares each region's growth in the top 5 employment, the top 5 employment shares, and population between 1997 and 2000 in the baseline and the no-mobility counterfactual. The changes in L_{nt} account for most of the variations in the top 5 employment, with changes in λ_{njt} explaining only about 1% of the total variation.

Larger amounts of sectoral reallocation into the top 5 sectors translated into higher real GDP growth, as detailed in Table 8. In the baseline, real GDP dropped by 8.78% in the year of the crisis, followed by a recovery. Higher mobility levels were associated with lower declines in real GDP at the time of the crisis and higher growth during the recovery. In the full-mobility scenario, cumulative growth four years after the crisis exceeded the baseline by 3.32 percentage points. Notably, the disparity between the baseline and full-mobility outcomes surpassed that between the baseline and no-mobility scenarios, reflecting the proximity of baseline mobility levels to those of no-mobility rather than full-mobility.

Moreover, the directional reductions demonstrated a more effective impact on real GDP growth compared to the common reductions (4.62% vs. 4.91%), despite lower mobility rates with the former (10.33% vs. 9.72%). This suggests that the effectiveness of migration policies to boost real GDP depends on both the magnitude and direction of reductions.

Higher mobility rates led to large dispersion in real GDP growth at the regional level, as indicated by the standard deviation of the geometric average of regional GDP growth in Panel B. To examine

Table 8: Real GDP Growth After the Crisis

	Baseline	No-mobility	Full-mobility	Decrease med. (common)	Decrease med. (directional)
Years since the crisis	(1)	(2)	(3)	(4)	(5)
	Panel A. Aggregate real GDP				
Avg. annual growth, $(\prod_{\tau=98}^{02} Y_{\tau}^{\tau})^{\frac{1}{5}}$ (%)	-0.32	-0.66	1.09	-0.09	-0.20
	Panel B. Regional real GDP				
Std. $\log(\prod_{\tau=98}^{02} \hat{Y}_{n\tau}^{\tau})^{\frac{1}{5}}$	0.042	0.037	0.076	0.044	0.047
$\hat{\beta}^{\text{GDP}}$	0.02	0.004	0.048	0.022	0.03
	(0.006)	(0.006)	(0.01)	(0.006)	(0.007)

Notes. This table reports the counterfactual results on aggregate and regional GDP growth.

these regional effects, I run the following regression:

$$y_{nt} = \alpha + \beta^{\text{GDP}} \text{Empsh}_{n,94}^{\text{top3}} + \epsilon_{nt},$$

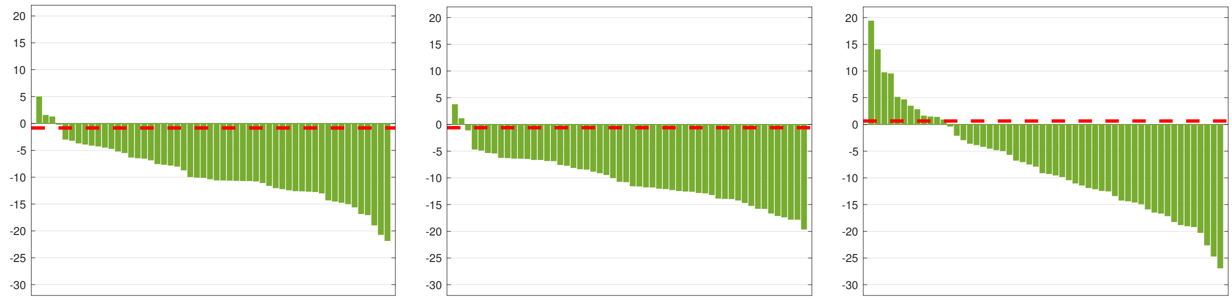
where the dependent variable is the average real GDP growth of region n. β^{GDP} is a regional elasticity of the average real GDP growth with respect to the initial top 5 employment shares. It turns out that higher mobility rates were associated with higher estimated β^{GDP}, indicating larger real GDP growth in regions with industrial compositions more oriented toward the top 5 sectors. This relationship emerged because larger migration inflows into these regions increased demand for the non-top 5 sectors and also lowered overall production costs through IO linkages. Consequently, higher mobility rates led to larger local multiplier effects, contributing to larger dispersion, as graphically illustrated in Figure 8.

5.2.2 Welfare Effects of the Crisis

Table 9 illustrate the aggregate and the regional welfare effects. Higher mobility rates tended to be associated with lower aggregate welfare loss from the crisis. The aggregate welfare changes mask large heterogeneity across regions, varying from around -35% to 15%. To examine the systematic relationship between the welfare effects and industrial composition, I run

$$\log(1 + \triangle V_{n,97}) = \alpha + \beta^{\text{wel}} \log \text{Empsh}_{n,94}^{\text{top3}} + \epsilon_n,$$

Figure 8. Migration and Regional Real GDP



A. Baseline B. No-mobility C. Free-mobility

Notes. Panels A, B, and C illustrate the geometric average of each region's real GDP growth between 1998 and 2002 under different mobility levels. The red dashed lines represent for the average aggregate real GDP growth between 1998 and 2002.

Table 9: Welfare Effects of the Crisis

	Baseline	No-mobility	Full-mobility	Decrease med. (common)	Decrease med. (directional)
	(1)	(2)	(3)	(4)	(5)
	Panel A. Aggregate welfare				
$\triangle V_{97}^{\text{agg}}$ (%)	-0.85	-0.61	-0.25	-0.54	-0.57
	Panel B. Regional welfare				
Std. $\log(1 + \triangle V_{n,97})$	0.102	0.110	0.099	0.101	0.101
β^{Wel}	0.049**	0.059**	0.048**	0.052**	0.052**
	(0.015)	(0.018)	(0.016)	(0.016)	(0.016)

Notes. This table reports the counterfactual results on the aggregate and regional welfare effects of the crisis.

where β^{wel} is an elasticity of the initial top 5 employment share to the welfare effects. Across different mobility levels, β^{wel} is positive, implying that regions with higher shares tended to experience less welfare loss.

Higher mobility rates were related to lower dispersion of the welfare effects across regions. This is because lower frictions allow households living in a region which was more exposed to the negative shocks to move to another that got relatively better off. On the other hand, households living in a region that got relatively better off after the crisis get worse off from lower migration frictions, because larger migration inflows into the region lower wages due to the increased labor supply. This channel is consistent with lower and higher values of β^{wel} in the no- and full-mobility counterfactuals, respectively, compared to the baseline. The welfare results suggest that policies promoting migration during the crisis may increase aggregate welfare but make some regions worse off.

6 Conclusion

This paper studies how internal migration responded to the 1998 South Korean crisis and its aggregate and regional consequences. I find that people migrated relatively more to regions who specialize in sectors that drove the recovery of the economy after the crisis and these regions experienced relatively larger employment growth. Using the model, I quantitatively find that higher mobility makes the economy adjust more flexibly to the crisis, but amplifies the distributional effects of the crisis. These findings suggest that tighter spatial linkages across factor markets can improve the flexibility of an economy, and that migration policies can be one of the policy options to stimulate economic recovery after large crises in emerging market economies.

References

Adão, Rodrigo, Costas Arkolakis, and Federico Esposito, "General Equilibrium Effects in Space: Theory and Measurement," *NBER Working Paper w25544*, 2020.

—, Michal Kolesár, and Eduardo Morales, "Shift-Share Designs: Theory and Inference," *Quarterly Journal of Economics*, 2019, *134* (4), 1949–2010.

Aguiar, Mark, "Investment, Devaluation, and Foreign Currency Exposure: The case of Mexico," *Journal of Development Economics*, 2005, *78* (1), 95–113.

Alessandria, George A., Sangeeta Pratap, and Vivian Yue, "Export Growth and Aggregate Dynamics in Large Devaluations," *Working Paper*, 2020.

Alessandria, George, Joseph P. Kaboski, and Virgiliu Midrigan, "Inventories, Lumpy Trade, and Large Devaluations," *American Economic Review*, 2010, *100* (5), 2304–2339.

Allen, Treb and Costas Arkolakis, "Trade and the Topography of the Spatial Economy," *Quarterly Journal of Economics*, 2014, *129* (2014), 1085–1139.

—, —, and Xiangliang Li, "On the Equilibrium Properties of Network Models with Heterogeneous Agents," *NBER Working Paper 27837*, 2020.

Andrews, Isaiah, James H. Stock, and Liyang Sun, "Weak Instruments in Instrumental Variables Regression: Theory and Practice," *Annual Review of Economics*, 2019, *11*, 727–753.

Artuc, Erhan, Paulo Bastos, and Eunhee Lee, "Trade, Jobs, and Worker Welfare," *Working Paper*, 2021.

—, Shubham Chaudhuri, and John Mclaren, "Trade Shocks and Labor Adjustment : A Structural Empirical Approach," *American Economic Review*, 2010, *100* (3), 1008–1045.

Ates, Sina T. and Felipe E. Saffie, "Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection," *American Economic Journal: Macroeconomics*, 2021, *13* (3), 304–356.

Auer, Raphael, Ariel T Burstein, Sarah Lein, and Jonathan Vogel, "Unequal Expenditure Switching: Evidence from Switzerland," *Working Paper*, 2022.

Autor, David H, David Dorn, and Gordon H Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

Balboni, Clare, "In Harm's Way? Infrastructure Investments and the Persistence of Coastal Cities," *Working Paper*, 2021.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen, "Inference on Treatment Effects after Selection among High-Dimensional Controls," *Review of Economic Studies*, 2014, *81* (2), 608–650.

Benguria, Felipe, Felipe Saffie, and Sergio Urzúa, "The Transmission of Commodity Price Super-Cycles," *NBER Working Paper 27589*, 2018.

Blanchard, Olivier Jean and Lawrence F. Katz, "Regional Evolutions," *Brookings Papers on Economic Activity*, 1992, *1992* (1), 1–75.

Blanco, Andres, Andres Drenik, and Emilio Zaratiegui, "Nominal Devaluations, Inflation and Inequality," *Working Paper*, 2022.

Blanco, Andrés, Bernardo Diaz de Astarloa, Andres Drenik, Christian Moser, and Danilo R. Trupkin, "The Evolution of the Earnings Distribution in a Volatile Economy: Evidence from Argentina," *Quantitative Economics*, 2022, *13* (4), 1361–1403.

Blaum, Joaquin, "Global Firms in Large Devaluations," *Working Paper*, 2018.

— , **Claire Lelarge, and Michael Peters**, "The Gains from Input Trade with Heterogeneous Importers," *American Economic Journal: Macroeconomics*, 2018, *10* (4), 77–127.

Bonadio, Barthélémy, Andreas M Fischer, and Philip Sauré, "The Speed of Exchange Rate Pass-Through," *Journal of the European Economic Association*, 2020, *18* (1).

Borusyak, Kirill, Rafael Dix-Carneiro, and Briak K Kovak, "Understanding Migration Responses to Local Shocks," *Working Paper*, 2022.

Bryan, Gharad and Melanie Morten, "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia," *Journal of Political Economy*, 2019, *127* (5), 2229–2268.

Burstein, Ariel, Eduardo Morales, and Jonathan Vogel, "Changes in Between-Group Inequality: Computers, Occupations, and International Trade," *American Economic Journal: Macroeconomics*, 2019, *11* (2), 348–400.

— , **Martin Eichenbaum, and Sergio Rebelo**, "Large Devaluations and the Real Exchange Rate," *Journal of Political Economy*, 2005, *113* (4), 742–784.

— , — , **and** — , "Modeling Exchange Rate Passthrough after Large Devaluations," *Journal of Monetary Economics*, 2007, *54* (2), 346–368.

Cadena, Brian C and Brian K Kovak, "Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 2016, *8* (1), 257–290.

Caliendo, Lorenzo, Fernando Parro, Esteban Rossi-Hansberg, and Pierre Daniel Sarte, "The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy," *Review of Economic Studies*, 2018, *85* (4), 2042–2096.

— , **Luca David Opromolla, Fernando Parro, and Alessandro Sforza**, "Goods and Factor Market Integration: A Quantitative Assessment of the EU Enlargement," *Journal of Political Economy*, 2021, *129* (12), 3491–3545.

— , **Maximiliano Dvorkin, and Fernando Parro**, "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica*, 2019, *87* (3), 741–835.

Carrère, Céline, Anja Grujovic, and Frédéric Robert-Nicoud, "Trade and Frictional Unemployment in the Global Economy," *Journal of the European Economic Association*, 2020, *18* (6), 2869–2921.

Chaney, Thomas, "Liquidity Constrained Exporters," *Journal of Economic Dynamics and Control*, 2016, *72*, 141–154.

Choi, Jaedo and Andrei A. Levchenko, "The Long-Term Effects of Industrial Policy," *NBER Working Paper 29263*, 2023.

— , — , **Dimitrije Ruzic, and Younghun Shim**, "Superstars or Supervillains? Large Firms in the South Korean Growth Miracle," *Working Paper*, 2023.

Colella, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig, "Inference with Arbitrary Clustering," *Working Paper*, 2021.

Conley, T. G., "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics*, 1999, *92* (1), 1–45.

Costinot, Arnaud and Andrés Rodríguez-Clare, "Trade Theory with Numbers: Quantifying the Consequences of Globalization," in "Handbook of International Economics," Vol. 4 2014, pp. 197–261.

Cravino, Javier and Andrei A Levchenko, "The Distributional Consequences of Large Devaluations," *American Economic Review*, 2017, *107* (11), 3477–3509.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum, "Global Rebalancing with Gravity: Measuring the Burden of Adjustment," *IMF Staff Papers*, 2008, *55* (3), 511–540.

di Giovanni, Julian, Andrei A. Levchenko, and Isabelle Mejean, "Foreign Shocks as Granular Fluctuations," *NBER Working Paper 28123*, 2020.

Diamond, Rebecca, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," 2016.

Dix-Carneiro, Rafael, "Trade Liberalization and Labor Market Dynamics," *Econometrica*, 2014, *82* (3), 825–885.

__ and Brian K. Kovak, "Trade Liberalization and Regional Dynamics," *American Economic Review*, 2017, *107* (10), 2908–2946.

__ and __ , "Margins of Labor Market Adjustment to Trade," *Journal of International Economics*, 2019, *117*, 125–142.

__ , Joao Paulo Pessoa, Ricardo Reyes-Heroles, and Sharon Trailberman, "Globalization, Trade Imbalances and Labor Market Adjustment," *NBER Working Paper 28315*, 2021.

Drenik, Andres, "Labor Market Dynamics After Large Devaluation," *Working Paper*, 2016.

__ , Gustavo Pereira, and Diego J. Perez, "Wealth Redistribution after Exchange Rate Devaluations," *American Economic Review Papers and Proceedings*, 2018, *108*, 552–556.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1749.

__ , __ , Brent Neiman, and John Romalis, "Trade and the Global Recession," *American Economic Review*, 2016, *106* (11), 3401–3438.

Eckert, Fabian, "Growing Apart: Tradable Services and the Fragmentation of the U.S. Economy," *Working Paper*, 2019.

Fan, Jingting, "Internal Geography, Labor Mobility, and the Distributional Impacts of Trade," *American Economic Journal: Macroeconomics*, 2019, *11* (3), 252–288.

Galle, Simon, Andres Rodriguez-Clare, and Moises Yi, "Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade," *Review of Economic Studies (Forthcoming)*, 2022.

Gervais, Antoine and J. Bradford Jensen, "The Tradability of Services: Geographic Concentration and Trade Costs," *Journal of International Economics*, 2019, *118*, 331–350.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 2020, *110* (8), 2586–2624.

Gopinath, Gita and Brent Neiman, "Trade Adjustment and Productivity in Large Crises," *American Economic Review*, 2014, *104* (3), 793–831.

Greenland, Andrew, John Lopresti, and Peter McHenry, "Import Competition and Internal Migration," *Review of Economics and Statistics*, 2019, *101* (1), 44–59.

Hakobyan, Shushanik and John McLaren, "Looking for Local Labor Market Effects of NAFTA," *Review of Economics and Statistics*, 2016, *98* (4).

Hao, Tongtong, Ruiqi Sun, Trevor Tombe, and Xiaodong Zhu, "The Effect of Migration Policy on Growth, Structural Change, and Regional Inequality in China," *Journal of Monetary Economics*, 2020, *113*, 112–134.

Head, Keith and John Ries, "Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade," *American Economic Review*, 2001, *91* (4), 858–876.

House, Christopher L, Christian Proebsting, and Linda L Tesar, "Regional Effects of Exchange Rate Fluctuations," *Journal of Money, Credit and Banking*, 2020, *52* (S2), 263–429.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones, and Peter J. Klenow, "The Allocation of Talent and U.S. Economic Growth," *Econometrica*, 2019, *87* (5), 1439–1474.

Imbert, Clément and John Papp, "Short-term Migration, Rural Public Works, and Urban Labor Markets: Evidence from India," *Journal of the European Economic Association*, 2020, *18* (2).

Kehoe, Timothy J. and Kim J. Ruhl, "Sudden Stops, Sectoral Reallocations, and the Real Exchange Rate," *Journal of Development Economics*, 2009, *89* (2), 235–249.

Kim, Ryan and Jonathan Vogel, "Trade Shocks and Labor Adjustment," *American Economic Review: Insights*, 2021, *3* (1), 115–130.

Kim, Yun Jung, Linda L Tesar, and Jing Zhang, "The Impact of Foreign Liabilities on Small Firms: Firm-level Evidence from the Korean Crisis," *Journal of International Economics*, 2015, *97* (2), 209–230.

Kleinman, Benny, Ernest Liu, and Stephen J. Redding, "Dynamic Spatial General Equilibrium," *NBER Working Paper 29101*, 2021.

Kohn, David, Fernando Leibovici, and Michal Szkup, "Financial Frictions and Export Dynamics in Large Devaluations," *Journal of International Economics*, 2020, *122*, 103257.

Kondo, Illenin O., "Trade-Induced Displacements and Local Labor Market Adjustments in the U.S.," *Journal of International Economics*, 2018, *114*, 180–202.

Kovak, Brian K, "Regional Effects of Trade Reform: What is the Correct Measure of Liberalization?," *American Economic Review*, 2013, *103* (5), 1960–1976.

Lagakos, David, Ahmed Mushfiq Mobarak, and Michael E Waugh, "The Welfare Effects of Encouraging Rural-Urban Migration," *Econometrica*, 2023, *91* (3), 803–837.

— **and Michael E Waugh**, "Selection, Agriculture, and Cross-Country Productivity Differences," *American Economic Review*, 2016, *103* (2), 948–980.

Lee, Eunhee, "Trade, Inequality, and the Endogenous Sorting of the Heterogeneous Workers," *Journal of International Economics*, 2020, *125*, 103–310.

Ma, Lin and Yang Tang, "Geography, Trade, and Internal Migration in China," *Journal of Urban Economics*, 2020, *115* (103181).

Mendoza, Enrique G., "Sudden Stops, Financial Crises, and Leverage," *American Economic Review*, 2010, *100* (5), 1941–1966.

Meza, Felipe and Erwan Quintin, "Factor Utilization and the Real Impact of Financial Crises," *The B.E. Journal of Macroeconomics*, 2007, *7* (1).

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak, "Internal Migration in the United States," *Journal of Economic Perspectives*, 2011, *25* (3).

Monras, Joan, "Economic Shocks and Internal Migration," *Working Paper*, 2015.

— , "Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis," *Journal of Political Economy*, 2020, *128* (8), 3017–3089.

Monte, Ferdinando, Stephen J. Redding, and Esteban Rossi-Hansberg, "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 2018, *108* (12), 3855–3890.

Montiel Olea, José Luis and Carolin Pflueger, "A Robust Test for Weak Instruments," *Journal of Business and Economic Statistics*, 2013, *31* (3), 358–369.

Moretti, Enrico, "Local Multipliers," *American Economic Review*, 2010, *100* (2), 373–377.

__ , "Real Wage Inequality," *American Economic Journal: Economic Policy*, 2017, *5* (1), 65–103.

Morten, Melanie and Jaqueline Oliveira, "The Effects of Roads on Trade and Migration: Evidence from a Planned Capital City," *NBER Working Paper 22158*, 2018.

Pellegrina, Heitor and Sebastian Sotelo, "Migration, Specialization, and Trade: Evidence from the Brazilian March to the West," *NBER Working Paper 28421*, 2021.

Pratap, Sangeeta and Carlos Urrutia, "Financial Frictions and Total Factor Productivity: Accounting for the Real Effects of Financial Crises," *Review of Economic Dynamics*, 2012, *15* (3), 336–358.

Queralto, Albert, "A Model of Slow Recoveries from Financial Crises," *Journal of Monetary Economics*, 2020, *114*, 1–25.

Rambachan, Ashesh and Jonathan Roth, "A More Credible Approach to Parallel Trends," *Review of Economic Studies*, 2023, *90* (5), 2555–2591.

Redding, Stephen J., "Goods Trade, Factor Mobility and Welfare," *Journal of International Economics*, 2016, *101*, 148–167.

Reyes-Heroles, Ricardo, "The Role of Trade Costs in the Surge of Trade Imbalances," *Working Paper*, 2016.

Rodriguez-Clare, Andres, Mauricio Ulate, and Jose P. Vasquez, "Trade with Nominal Rigidities: Understanding the Unemployment and Welfare Effects of the China Shock," *NBER Working Paper 27905*, 2022.

Schmitt-Grohé, Stephanie and Martín Uribe, "Downward Nominal Wage Rigidity, Currency Pegs, and Involuntary Unemployment," *Journal of Political Economy*, 2016, *124* (5), 1466–1514.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J. de Vries, "An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production," *Review of International Economics*, 2015, *23* (3), 575–605.

Tombe, Trevor and Xiaodong Zhu, "Trade, Migration, and Productivity: A Quantitative Analysis of China," *American Economic Review*, 2019, *109* (5), 1843–1872.

Topalova, Petia, "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India," *American Economic Journal: Applied Economics*, 2010, *2* (4), 1–41.

Traiberman, Sharon, "Occupations and Import Competition: Evidence from Denmark," *American Economic Review*, 2019, *109* (12), 4260–4301.

Uribe, Martin and Stephanie Schmitt-Grohé, *Open Economy Macroeconomics*, Princeton University Press, 2017.

ONLINE APPENDIX

(NOT FOR PUBLICATION)

A Data

I describe the data used for empirical and quantitative analysis.

- *Region-sector employment* I use the Census on Establishment to construct region-sector employment shares. The Census on Establishment covers the universe of formal establishments with one or more employees except for agriculture, forestry, and fisheries businesses by individual owners and establishments related to national defense, housekeeping services, and international and foreign organizations. On average, approximately 2.9 million establishments are covered by the data set across the sample period from 1994 to 2002. The data set has information on geographical location, sectors, and employment of establishments. I convert the Korean Sector Industry Code (KSIC) to the ISIC Rev 3. The sample in 1994 is used to construct the initial employment shares for the shift-share regressor of the empirical analysis.

- *Region-sector gross output* In order to construct region-sector gross output, I combine the WIOD IO tablesm the state-sector level gross output data from Statistics Korea, and the Census of Establishment. From the WIOD IO tables, I obtain the national-level sectoral gross output. I allocate this national-level sectoral gross output across states using the state-level data. Within state-sector, I allocate reion-sector gross output using the region-sector employment from the Census of Establishment. Specifically, region-sector gross output is calculated as $\mathrm{GO}_{njt} = \tilde{\omega}_{nt}^{j} \times \mathrm{GO}_{jt}^{WIOD}$. GO_{jt}^{WIOD} is sector j's gross output obtained from the WIOD. $\tilde{\omega}_{nt}^{j}$ is a share of sector j employment of region n to total sector j employment: $\tilde{\omega}_{nt}^{j} = \frac{\mathrm{Emp}_{njt}}{\sum_m \mathrm{Emp}_{mjt}}$. The allocation from state- to region-level is unlikely to produce large measurement errors, because the state-level data has the exact information on the major 7 cities which cover about 50% of total population. Each major 7 city is classified as an individual state according to the Korean administrative district. The major 7 cities are Seoul, Busan, Incheon, Gwangju, Daejeon, Ulsan, and Daegu.

- *Region-to-region migration flows* I construct region-to-region migration flows using the internal migration and population data sets obtained from the Statistics Korea. Migration flows are calculated as the total number of migrants between origin and destination regions divided by lagged populations of origin regions. Own migrants are calculated as the lagged population minus the sum of migrants to other regions. Given that my focus is the working population, I restrict the samples of populations and migration flows to people aged between 20 and 55 years.

- *Sectoral trade data and IO tables* Sectoral trade data is obtained from the WIOD between 1995 and 2002. Countries except for South Korea are aggregated and classified as the Rest of the World (ROW). Trade data and IO tables in 1993 used to construct the initial sectoral export-intensities, SecEX_{njt_0}, are obtained from the Bank of Korea.

- *Sector classification* I categorize sectors into 15 sectors. This grouping is reported in Table A1.

- *Region-sector real capital stock* This data is only used for the quantitative analysis with the model extended to incorporate capital accumulation dynamics. I construct region-sector real capital stock by combining the Census of Establishment, the Mining and Manufacturing Survey, the WIOD Socio–Economic Accounts (WIOD-SEA), and the International Monetary Fund (IMF) Investment and Capital Stock Database (IMF-ICSD). I first allocate the aggregate real capital stock from the IMF-ICSD using country-sector level nominal capital stock shares from the WIOD-SEA: $K_{jt} = \tilde{\omega}_{jt}^K \times K_t$, where K_t is the aggregate real capital stock from the IMF-ICSD and $\tilde{\omega}_{jt}^K$ is a share of sector j nominal capital stock to the total nominal capital stock across sectors from the WIOD-SEA.

  The Mining and Manufacturing Survey covers the universe of formal establishments with more than five employees in the mining and manufacturing sectors, which are a subset of the Census of Establishment. However, when compared with the Census of Establishment, the Mining and Manufacturing Sector Survey has more detailed establishment-level variables including fixed assets. Using the Mining and Manufacturing Survey that has information on nominal fixed assets of manufacturing establishments, I calculate region-sector fixed asset shares:

  $$\tilde{\omega}_{njt}^K = \frac{\text{Fassets}_{njt}}{\sum_{n' \in \mathcal{N}} \text{Fassets}_{n'jt}},$$

  where Fassets_{njt} is the sum of fixed assets of sector j establishments in region n. Then, I allocate region-sector real capital stock using these computed shares: $K_{njt} = \tilde{\omega}_{njt}^K \times K_{jt}$. For the non-manufacturing sectors, I do not have information on region-sector level nominal fixed assets, so I use region-sector employment shares to allocate region-sector real capital stock.

- *Data used for constructing the regional exposure to the balance sheet effect* KIS-VALUE is used for constructing industry-level exposure to the balance sheet effects. It is similar to US Compustat and has detailed financial information. However, its advantage over US Compustat is that it includes medium-sized firms that are not publicly traded. I obtain five variables from KIS-VALUE: firm-level employment, foreign currency-denominated debt, foreign currency denominated assets, total assets, and total liabilities.

- *Data used for constructing the amenity index* Amenity index is computed using Population Census, which is a 2% random sample of total population, Census of Establishment, and the Mining and Manufacturing Survey. From these sources, I calculate the number of retail establishments, the number of establishments in education service per capita, shares of workers using public transportation for commuting, the number of factories per capita, and shares of white collar occupation workers, and the number of business service establishments per capita.

Table A1: Sector Classification

Aggregated Industry	Industry
1. Commodity	Agriculture, hunting and forestry (A), Fishing (B) Mining and quarrying (C)
2. Food, Beverages, and Tobacco*	Food products and beverages (15), Tobacco products (16)
3. Textiles, Apparel, & Leather*	Textiles (17), Apparel (18) Leather, luggage, handbags, saddlery, harness, and footwear (19)
4. Wood, Paper & Printing*	Wood and of products, cork (20) Paper and paper products (21) Publishing and printing (22)
5. Chemicals, Petrochemicals, and Rubber and Plastic Products*	Coke, refined petroleum products and nuclear fuel (23) Chemicals and chemical products (24) Rubber and plastics products (25)
6. Non-Metallic Mineral Products*	Other non-metallic mineral products (26)
7. Basic and Fabricated Metals*	Basic metals (27), Fabricated metals (28)
8. Electrical Equipment*	Office, accounting and computing machinery (30) Electrical machinery and apparatus n.e.c. (31) Ratio, television and communication equipment and apparatus (32) Medical, precision, and optical instruments, watches and clocks (33)
9. Machinery and Transport Equipment*	Machinery and equipment n.e.c. (29) Motor vehicles, trailers, and semi trailers (34) Other transport equipment (35)
10. Manufacturing n.e.c.*	Manufacturing n.e.c. (36), Recycling (37)
11. Utilities	Electricity, gas and water supply (E)
12. Construction	Construction (F)
13. Whole and Retail	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods (G)
14. Transport Service	Land transport; transport via pipelines (60) Water transport (61), Air transport (62) Supporting and auxiliary transport activities; activities of travel agencies (63)
15. Other Service	Hotels and restaurants (H) Post and telecommunications (64), Financial intermediation (J) Real estate, renting, and business activities (K) Public administration and defense (L); compulsory social security (L) Education (M), Health and social work (N) Other community, social and personal service activities (O) Activities of private households as employers and undifferentiated production activities of private households (P)

Note. The codes inside the parenthesis denote the ISIC rev 3.1. industry codes. Superscript * denotes for manufacturing sectors.

B Empirics

Table B2: Principal Component Analysis for Amenity Index

Variables	Loading
Log shares of white collar occupation workers	0.45
Log of the number of retail service establishment per capita	0.45
Log of the number of education service establishment per capita	0.43
Log shares of workers using public transportation for commuting	0.45
Log of the number of business service establishments per capita	0.45
Log of the number of factories per capita	-0.08

Note. This table reports loadings to create the overall amenity index.

Table B3: Robustness. No Commuting Effects

Dep.	Commuting Inflows		Commuting Outflows	
	(1)	(2)	(3)	(4)
$\text{Bartik}_{n(m)t_0}$	0.22	0.30	0.05	0.17
	(0.21)	(0.26)	(0.14)	(0.12)
Origin-Year FE	✓	✓		
Destination-Year FE			✓	✓
Controls		✓		✓
Adj. R^2	0.29	0.37	0.39	0.47
Cluster1	53	53	53	53
Cluster2	53	53	53	53
N	466	466	466	466

Note. Standard errors, two-way clustered at the origin and destination levels, are in parenthesis. *: $p < 0.1; ** :$ $p < 0.05$; ***: $p < 0.01$. The dependent variables are changes in log commuting shares between regions. $\text{Bartik}_{n(m)t_0}$ is the Bartik shock. In columns 2 and 4, I control for additional variables including log initial employment, changes in migration flows between 1995 and 1996, the regional exposure to the balance sheet effect (eq., 3.3), changes in log unemployment rate between 1995 and 2000, differences of industrial composition between origin and destination regions (eq., 3.4), and changes in the amenity index between 1995 and 2000. Columns 1-2 and 3-4 include origin and destination fixed effects, respectively.

Table B4: Robustness. Excluding Pairs with Distance Less than 100km. Employment Responses to the Crisis

Dep.	Inflows ($\geq$ 100km)		Outflows ($\geq$ 100km)	
	(1)	(2)	(3)	(4)
$\text{Bartik}_{n(m)t_0}$	0.08^{**}	0.06^{*}	-0.05^{***}	-0.05^{**}
	(0.03)	(0.03)	(0.02)	(0.02)
Origin-Year FE	✓	✓		
Destination-Year FE			✓	✓
Controls		✓		✓
Adj. R^2	0.20	0.21	0.29	0.31
Cluster (Origin)	54	54	54	54
Cluster (Dest.)	54	54	54	54
N	2082	2082	2082	2082

Note. Standard errors, two-way clustered at the origin and destination levels, are in parenthesis. *: $p < 0.1$; $** : p < 0.05$; ***: $p < 0.01$. The table reports the OLS estimates of eq. (3.1) for the subsample that excludes migration pairs within 100km distance. The dependent variables are changes in log migration shares between regions. $\text{Bartik}_{n(m)t_0}$ is the Bartik shock. In column 2 and 4, I control for additional variables including log initial employment, changes in migration flows between 1995 and 1996, the regional exposure to the balance sheet effect (eq., 3.3), changes in log unemployment rate between 1995 and 2000, differences of industrial composition between origin and destination regions (eq., 3.4), and changes in the amenity index between 1995 and 2000. Columns 1-2 and 3-4 include origin and destination fixed effects, respectively.

Table B5: Robustness. Alternative Forms of Clustering. Migration Responses to the Crisis

Dep.	Inflows		Outflows	
	(1)	(2)	(3)	(4)
$\text{Bartik}_{n(m)}$	0.09^{***}	0.07^{**}	-0.04^{***}	-0.04^{***}
Baseline, two-way cluster at the origin & destination levels, SE	(0.03)	(0.03)	(0.01)	(0.02)
Baseline, two-way cluster at the origin & destination levels, 95% CI	[0.03,0.15]	[0.01,0.13]	[−0.07,−0.01]	[−0.08,−0.01]
Cluster at the origin (or destination) level, SE	(0.03)	(0.03)	(0.01)	(0.02)
Cluster at the origin (or destination) level, 95% CI	[0.03,0.15]	[0.01,0.13]	[−0.07,−0.01]	[−0.07,−0.01]
Conley (1999) 100km spatial HAC, SE	(0.01)	(0.01)	(0.00)	(0.01)
Conley (1999) 100km spatial HAC, 95% CI	[0.07,0.10]	[0.06,0.08]	[−0.05,−0.04]	[−0.06,−0.03]
Adão et al. (2019) Shift-share adj., SE	(0.01)	(0.01)	(0.00)	(0.01)
Adão et al. (2019) Shift-share adj., 95% CI	[0.06,0.11]	[0.05,0.09]	[−0.05,−0.04]	[−0.06,−0.03]
Controls		✓		✓
N	54	54	54	54

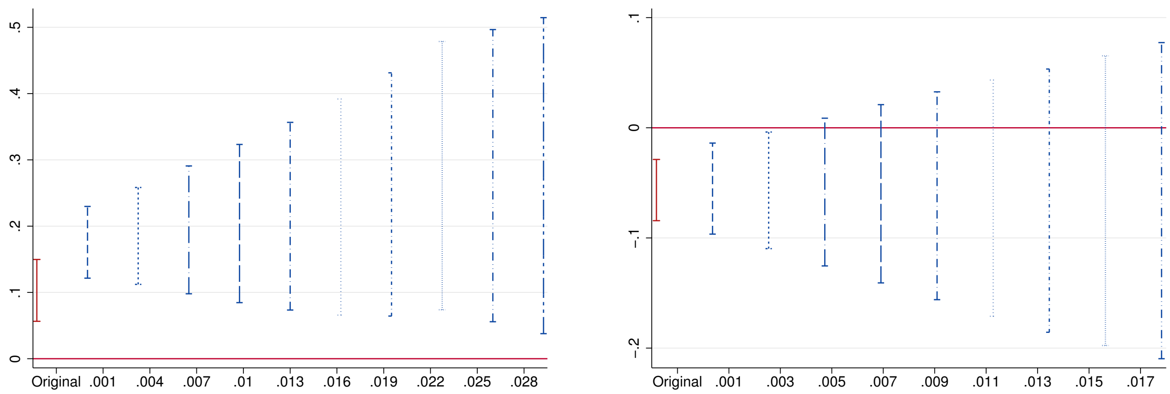
Note. This table reports robustness checks for alternative forms of clustering. Row 1 report the baseline estimates. Rows 2 and 3 report standard errors and 95% confidence intervals based on robust standard errors; rows 4 and 5, based on the Conley (1999) spatial HAC with wide bandwidths of 100km; and rows 6 and 7, based on the Adão et al. (2019) adjustment more shift-shares. Columns 2, 4, and 6 include changes in dependent variables between 1995 and 1997, the regional exposure to the balance sheet effect, changes in log unemployment rates between 1995 and 2000, and changes in the amenity index between 1995 and 2000.

Table B6: Robustness. Post-Double LASSO Selection. Migration Responses to the Crisis

	(1)	(2)
$\text{Bartik}_{n(m)}$	0.08^{***}	-0.06^{***}
	(0.03)	(0.02)
Origin FE	✓	
Destination FE		✓
# Cluster (Origin or destination)	54	54
N	2914	2914

Note. Robust standard errors are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Dependent variables are changes in migration flows between 1997 and 2000. Column 1 and 2 include origin and destination fixed effects, respectively, I choose optimal controls among changes in dependent variables between 1995 and 1997, changes in log unemployment rates between 1995 and 2000, changes in the amenity index between 1995 and 2000, and their polynomials and interaction terms up to the third order, using the Belloni et al. (2014) post-double LASSO selection. In both columns 1 and 2, two controls were selected by the LASSO procedure, the regional exposure to the balance sheet effects and its interaction with changes in log unemployment rates between 1995 and 2000.

Figure B9. Robustness. Sensitivity Analysis for Potential Violations to the Parallel Trend Assumption. Event Study. Migration Responses to the Crisis

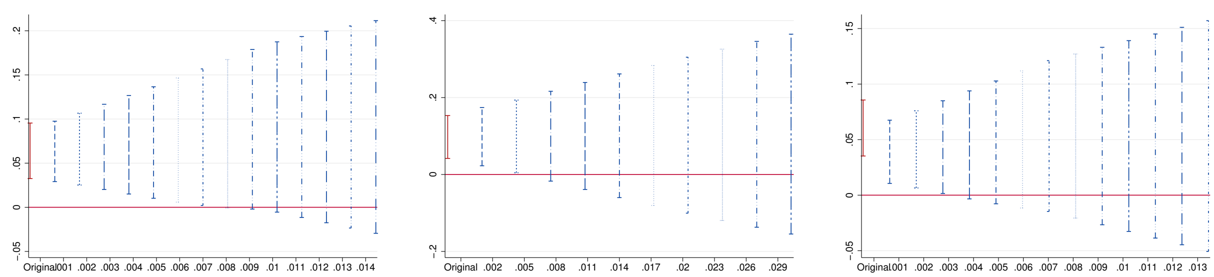


A. Migration inflow

B. Migration outflow

Note. This figure presents results of the sensitivity checks for potential violations of the parallel trend assumption based on the approach developed by Rambachan and Roth (2023). The figure reports the estimated 90% confidence intervals of the coefficient in 2000 for different levels of M in the axis. The maximum values of M are set to the standard error of the estimates in 2000.

Figure B10. Robustness. Sensitivity Analysis for Potential Violations to the Parallel Trend Assumption. Event Study. Employment Responses to the Crisis



A. Log total emp.

B. Top 5 emp.

C. Log non top 5 emp.

Note. This figure presents results of the sensitivity checks for potential violations of the parallel trend assumption based on the approach developed by Rambachan and Roth (2023). The figure reports the estimated 90% confidence intervals of the coefficient in 2000 of equation (3.7) for different levels of M in the axis. The maximum values of M are set to the standard error of the estimates in 2000.

Table B7: Rotemberg Weights

Dep.	Inflows				Outflows			
	$\hat{\alpha}_j$	$\hat{\beta}_j$	$\hat{\alpha}_j$	$\hat{\beta}_j$	$\hat{\alpha}_j$	$\hat{\beta}_j$	$\hat{\alpha}_j$	$\hat{\beta}_j$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food, Beverages, and Tobacco*	−0.01	−0.00	−0.01	0.07	−0.01	−0.15	−0.01	−0.10
Non-Metallic Mineral Products*	0.00	−0.05	0.00	−0.38	0.00	2.21	0.00	0.11
Basic and Fabricated Metals*	0.04	0.16	0.02	0.23	0.04	−0.09	0.02	−0.14
Manufacturing n.e.c.*	0.04	0.24	0.06	0.13	0.04	−0.11	0.06	−0.09
Commodity	−0.01	0.11	−0.01	0.11	−0.01	−0.07	−0.01	−0.09
Chemicals*	0.07	0.16	0.01	0.12	0.07	−0.05	0.01	−0.09
Utilities	−0.00	0.18	−0.00	0.26	−0.00	−0.04	−0.00	−0.00
Electrical Equipment*	0.56	0.10	0.49	0.03	0.56	−0.04	0.49	−0.05
Construction	−0.00	0.12	−0.00	0.04	−0.00	−0.05	−0.00	−0.06
Other Service	−0.03	0.12	−0.02	0.08	−0.03	−0.05	−0.02	−0.06
Whole and Retail	−0.09	0.15	−0.04	0.03	−0.09	−0.05	−0.04	−0.09
Textiles, Apparel, & Leather*	0.32	0.05	0.47	0.06	0.32	−0.05	0.47	−0.04
Transport Service	−0.05	0.14	0.02	0.03	−0.05	−0.04	0.02	0.01
Machinery and Transport Equipment*	0.15	0.13	−0.00	−1.75	0.15	−0.09	−0.00	3.19
Wood, Paper & Printing*	0.01	0.28	0.00	0.59	0.01	−0.02	0.00	0.21
Controls			✓	✓			✓	✓

Note. This table reports the Rotemberg weights $\hat{\alpha}_j$ and the just-identified IV estimators based on each share $\hat{\beta}_j$ (Goldsmith-Pinkham et al., 2020). Superscript * denotes for manufacturing sectors. In columns 1-4 and 5-8, the specifications are $\triangle \ln \mu_{nmt} = \beta \text{Bartik}_{mt_0} + \mathbf{X}'_{mt}\boldsymbol{\gamma} + \delta_n + \triangle \epsilon_{nmt}$ and $\triangle \ln \mu_{nmt} = \beta \text{Bartik}_{nt_0} + \mathbf{X}'_{nt}\boldsymbol{\gamma} + \delta_m + \triangle \epsilon_{nmt}$, respectively. In columns 3-4 and 7-8, additional controls of origin and destination regions, including the initial log population and employment, the pretrends of changes in log migration shares between 1995 and 1996, the regional exposure to balance sheet effects, the changes in unemployment between 1995 and 2000, and the changes in the amenity index between 1995 and 2000, are included, respectively.

Table B8: Summary of Rotemberg Weights

Dep.	Inflows		Outflows	
	(1)	(2)	(3)	(4)
Share of $\hat{\alpha}_j < 0$	0.47	0.47	0.47	0.47
Share of the sum of top 5 largest $\hat{\alpha}_j$ to $\sum_{j=1}^{J} \lvert\hat{\alpha}_j\rvert$	0.97	0.97	0.97	0.96
$\sum_{j\mid\hat{\alpha}_j<0} \hat{\alpha}_j \hat{\beta}_j$	0.12	0.06	-0.06	-0.05
$\sum_{j\mid\hat{\alpha}_j>0} \hat{\alpha}_j \hat{\beta}_j$	-0.02	0.00	0.01	-0.01
Controls		✓		✓

Note. This table reports the summary of the Rotemberg weights $\hat{\alpha}_j$ and the just-identified IV estimators based on each share $\hat{\beta}_j$ (Goldsmith-Pinkham et al., 2020). In columns 1-2 and 3-4, the specifications are $\triangle \ln \mu_{nmt} = \beta \text{Bartik}_{mt_0} + \mathbf{X}'_{mt}\boldsymbol{\gamma} + \delta_n + \triangle\epsilon_{nmt}$ and $\triangle \ln \mu_{nmt} = \beta \text{Bartik}_{nt_0} + \mathbf{X}'_{nt}\boldsymbol{\gamma} + \delta_m + \triangle\epsilon_{nmt}$, respectively. In columns 3 and 4, additional controls of origin and destination regions, including the initial log population and employment, the pretrends of changes in log migration shares between 1995 and 1996, the regional exposure to balance sheet effects, the changes in unemployment between 1995 and 2000, and the changes in the amenity index between 1995 and 2000, are included, respectively.

Table B9: Bartik Diagnostics. Correlations between Initial Shares and Observables

Dep.	Top 5 emp. shares in 1994			
	(1)	(2)	(3)	(4)
$\text{Empsh}_{n,94}^{\text{top5BS}}$	0.02			-0.03
	(0.12)			(0.13)
$\ln \text{Unemp}_{n,95}$		0.18		0.15
		(0.11)		(0.13)
$\text{Amenity}_{n,95}$			0.15	0.10
			(0.11)	(0.13)
N	54	54	54	54

Note. Robust standard errors are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. The dependent variables are employment shares of the top 5 most export-intensive manufacturing sectors. $\text{Empsh}_{n,94}^{\text{top5BS}}$ is an employment share in the top 5 sectors that are most vulnerable to the balance sheet effects, ranked based on $\text{BS}_{j,94}$. $\ln \text{Unemp}_{n,95}$ is log unemployment rate in 1995. $\text{Amenity}_{n,95}$ is the amenity index in 1995. All variables are standardized.

Table B10: Robustness. Alternative Forms of Clustering. Employment Responses to the Crisis

Dep.	△ log total emp.		△ log top 5 emp.		△ log non-top 5 emp.	
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik$_n$	0.05	0.04	0.07	0.07	0.04	0.03
Baseline SE	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)
Baseline 95% CI	[0.02,0.08]	[0.01,0.08]	[0.01,0.13]	[−0.01,0.14]	[0.02,0.07]	[0.00,0.05]
Conley (1999) 100km spatial HAC, SE	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Conley (1999) 100km spatial HAC, 95% CI	[0.02,0.08]	[0.01,0.08]	[0.02,0.12]	[0.00,0.13]	[0.02,0.06]	[0.01,0.05]
Adão et al. (2019) Shift-share adj., SE	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)
Adão et al. (2019) Shift-share adj., 95% CI	[0.01,0.08]	[0.01,0.13]	[0.01,0.13]	[−0.01,0.14]	[0.02,0.07]	[0.00,0.05]
Controls		✓		✓		✓
N	54	54	54	54	54	54

Note. This table reports robustness checks for alternative forms of clustering. Row 1 report the baseline estimates. Rows 2 and 3 report standard errors and 95% confidence intervals based on robust standard errors; rows 4 and 5, based on the Conley (1999) spatial HAC with wide bandwidths of 100km; and rows 6 and 7, based on the Adão et al. (2019) adjustment more shift-shares. Columns 2, 4, and 6 include changes in dependent variables between 1995 and 1997, the regional exposure to the balance sheet effect, changes in log unemployment rates between 1995 and 2000, and changes in the amenity index between 1995 and 2000.

Table B11: Robustness. Post-Double LASSO Selection. Employment Responses to the Crisis

Dep.	△ log total emp. (1)	△ log top 5 emp. (2)	△ log non-top 5 emp. (3)
Bartik$_n$	0.05***	0.07**	0.03**
	(0.01)	(0.03)	(0.01)
N	54	54	54

Note. Robust standard errors are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. I choose optimal controls among changes in dependent variables between 1995 and 1997, changes in log unemployment rates between 1995 and 2000, changes in the amenity index between 1995 and 2000, and their polynomials and interaction terms up to the third order, using the Belloni et al. (2014) post-double LASSO selection.

C Theory

C.1 Welfare

I denote V_{nt} and V_{nt}^c as the present discounted value of utility at period t in region n under the baseline and counterfactual shocks. Superscript c denotes counterfactual variables. I can write the baseline expected lifetime utility of living in region n at period t as

$$V_{nt} = \ln C_{nt} + \beta V_{n,t+1} + \nu \ln\left(\sum_m \exp(\beta(V_{m,t+1} - V_{n,t+1}) - \tau_{nmt})^{\frac{1}{\nu}}\right)$$

where the second term on the RHS of the above equation is the option value of beginning at region n at period t. Using that

$$\mu_{nnt} = \frac{\exp(\beta V_{n,t+1})^{\frac{1}{\nu}}}{\sum_m \exp(\beta V_{m,t+1} - \mu_{nmt})^{\frac{1}{\nu}}},$$

the option value can be expressed as own migration share:

$$\nu \ln\left(\sum_m \exp(\beta(V_{m,t+1} - V_{n,t+1}) - \tau_{nmt})^{\frac{1}{\nu}}\right) = -\nu \ln \mu_{nnt}.$$

Plugging this into the value function, I can obtain $V_{nt} = \ln C_{nt} + \beta V_{n,t+1} - \nu \ln \mu_{nnt}$. Iterating yields

$$V_{nt} = \sum_{s=t}^{\infty} \beta^{s-t} \ln(C_{ns}) - \nu \sum_{s=t}^{\infty} \beta^{s-t} \ln \mu_{nns}.$$

Using the above expression, I can express the lifetime utilities in the baseline and the counterfactual economy as follows:

$$V_{nt} = \sum_{s=t}^{\infty} \beta^{s-t} \ln\left(\frac{C_{ns}}{(\mu_{nns})^{\nu}}\right), \qquad V_{nt}^c = \sum_{s=t}^{\infty} \beta^{s-t} \ln\left(\frac{C_{ns}^c}{(\mu_{nns}^c)^{\nu}}\right).$$

Note that the amenity shocks are the same in both baseline and counterfactual economies. I measure the changes in welfare between the baseline and the counterfactual in terms of compensating variation, defined as the scalar δ_n^{wel} that satisfies

$$\sum_{s=t}^{\infty} \beta^{s-t} \ln\left(\frac{\delta_n^{wel} C_{ns}}{(\mu_{nns})^{\nu}}\right) = V_{nt}^c.$$

Rearranging the equation,

$$\ln \delta_n^{wel} = (1-\beta) \sum_{s=t}^{\infty} \beta^{s-t} \ln\left(\frac{(I_{ns}^c / I_{ns})}{(P_{ns}^c / P_{ns})(\mu_{nns}^c / \mu_{nns})^{\nu})}\right),$$

which can be rewritten as

$$\ln \delta_n^{wel} = (1-\beta)\sum_{s=t}^{\infty} \beta^{s-t} \ln\left(\frac{\hat{I}_{ns}^c}{\hat{P}_{ns}^c(\hat{\mu}_{nns}^c)^{\nu}}\right),$$

where $\hat{x}_t^c$ denotes changes of variable x between the baseline and counterfactual economies in given time: $\hat{x}_t^c = x_t^c/x_t$.

C.2 Balance Sheet Effects

In this section, I develop a one-period model of firms operating under credit constraints to illustrate that productivity shocks A_{njt} can capture balance sheet effects. The model is based on Kim et al. (2015) and I will follow their notations.

The setup is the same with the baseline model except for credit constraints. The crisis is characterized as a large depreciation in the Korean won, and the percentage increase in the exchange rate is denoted as $\triangle e_{won/\$}$. Before the crisis occurs, each perfectly competitive firm in region-sector nj has an initial net worth of N_{njt_0} and a net foreign debt d_{njt_0}. The net worth after the crisis is $n_{njt_1} = n_{njt_0} - d_{njt_0}\triangle e_{won/\$}$.

Firms are subject to working capital constraints. The working capital needed to finance firms' input costs can be covered by either their net worth or bank loan b_{njt_1}:

$$W_{njt_1}H_{njt_1} + \sum_{k=1}^{J} P_{nkt_1}M_{nkt_1} = n_{njt_1} + b_{njt_1}.$$

Firms may borrow from banks at the rate $r_{t_1}(n_{njt_1}, A_{njt_1}) = r_{t_1}^f(1+\eta(n_{njt_1}, A_{njt_1}))$. $r_{t_1}^f$ is the world risk free rate. $\eta(n_{njt_1}, A_{njt_1})$ is the financing premium that decreases in productivity A_{njt_1} and net worth n_{njt_1}.

Solving the cost minimization problem yields

$$c_{njt_1} = \frac{n_{njt_1} + b_{njt_1}r_{t_1}(n_{njt_1}, A_{njt_1})}{n_{njt_1} + b_{njt_1}} \frac{W_{njt_1}^{\gamma_j^H}\prod_k P_{nkt_1}^{\gamma_j^k}}{A_{njt_1}}.$$

The first-term captures the balance sheet effect. After the crisis, because firms' net worth decreases ($n_{njt_0} > n_{njt_1}$), larger shares of input expenditures are subject to working capital. Also, interest rate becomes higher due to lower net worth. Because r_{t_1} and A_{njt} enters the unit cost isomorphically, without additional data moments, they cannot be separately identified.

D Quantification

D.1 Regression Model of Migration Elasticity

In this section, I describe the derivation and estimation procedure of eq. (4.17). From eq. (4.9) and (4.10), I can derive the following equation:

$$V_{nt} = \ln C_{nt} - \nu \ln \mu_{nmt} + \beta V_{m,t+1} - \tau_{nmt}, \quad \forall n, m.$$

Using the above equation for pairs nn and nm and subtracting one from the other,

$$\ln \frac{\mu_{nmt}}{\mu_{nnt}} = \frac{\beta}{\nu}(V_{m,t+1} - V_{n,t+1}) - \frac{1}{\nu}\tau_{nmt}$$

Using eq. (4.9), the above expression can be written as

$$\ln \frac{\mu_{nmt}}{\mu_{nnt}} = \frac{\beta}{\nu} \ln \frac{I_{m,t+1}/P_{m,t+1}}{I_{n,t+1}/P_{n,t+1}} + \frac{\beta}{\nu}\Bigg(\nu \ln \sum_{n'} \exp(\beta V_{n',t+2} - \tau_{mn',t+1}) - \nu \ln \sum_{n'} \exp(\beta V_{n',t+2} - \tau_{nn',t+1})\Bigg) - \frac{1}{\nu}\tau_{nmt}.$$

Using eq. (4.10) and subtracting and adding $\beta V_{m,t+2} + B_{m,t+1} - \tau_{mn,t+1}$ on the right-hand side of the above equation, I obtain that

$$\ln \frac{\mu_{nmt}}{\mu_{nnt}} = \frac{\beta}{\nu} \ln \frac{I_{m,t+1}/P_{m,t+1}}{I_{n,t+1}/P_{n,t+1}} + \beta \ln \frac{\mu_{mn,t+1}}{\mu_{mm,t+1}} + \frac{1}{\nu}(\beta\tau_{mn,t+1} - \tau_{nm,t}).$$

Migration frictions can be decomposed into time-invariant and time-varying components: $\tau_{nmt} = \tilde{\tau}_{nm} + \tilde{\tau}_{nmt}$. This gives me the following estimable regression model:

$$\ln \frac{\mu_{nmt}}{\mu_{nnt}} = \frac{\beta}{\nu} \ln \frac{I_{m,t+1}/P_{m,t+1}}{I_{n,t+1}/P_{n,t+1}} + \beta \ln \frac{\mu_{mn,t+1}}{\mu_{mm,t+1}} + \delta_{nm} + \tilde{\epsilon}_{nmt}.$$

The pair time-invariant fixed effects δ_{nm} absorb time invariant migration frictions: $(\beta - 1)/\nu \times \tilde{\tau}_{nm}$. $\tilde{\epsilon}_{nmt}$ is the structural error term that is a function of time-varying migration friction shocks: $\tilde{\epsilon}_{nmt} = (1/\nu) \times (\beta\tilde{\tau}_{mn,t+1} - \tilde{\tau}_{nmt})$.

Estimating eq. (4.17) requires information on regional price levels. I construct the regional price levels using the data on the regional CPI and housing prices which are obtained from the Statistics Korea. The regional CPI data is only available for a few regions, whereas the regional housing prices are available for all regions. Therefore, following Moretti (2017), I impute the CPI for regions with missing CPI. For the subset of regions with non-missing CPI, I run the following regression:

$$gCPI_{n,t+1} = \pi \times gHP_{n,t+1} + \delta_t + \epsilon_{nt},$$

where $gCPI_{n,t+1}$ and $gHP_{n,t+1}$ are growth of CPI and housing price in region n between t and $t+1$. Using the estimated coefficients $\hat{\pi}$ and $\hat{\delta}_t$ and housing prices, I impute the growth of CPI for missing regions and compute CPI after normalizing the 1992 level to one.

D.2 Shock Formulation of the Model

Following Caliendo et al. (2019), I break down the equilibrium into two parts: a static equilibrium in which goods and factor market clearing conditions hold, taking populations and capital stock as given, and a dynamic equilibrium that solves forward-looking migration decisions of households.

Static equilibrium Unit costs are expressed as:

$$\hat{c}_{nj,t+1} = \frac{1}{\hat{A}_{nj,t+1}} (\hat{W}_{nj,t+1})^{\gamma_j^H} \prod_{k=1}^{J} (\hat{P}_{nj,t+1})^{\gamma_j^k}.$$

Price indices are expressed as:

$$(\hat{P}_{nj,t+1})^{1-\sigma} \sum_{m\in\mathcal{N}} \pi_{mnt}^{j} (\hat{c}_{nj,t+1})^{1-\sigma} + \pi_{Fnt}^{j} (\hat{P}_{j,t+1}^{F})^{1-\sigma}.$$

Domestic trade shares are

$$\hat{\pi}_{mn,t+1}^{j} = \left(\frac{\hat{c}_{mj,t+1}}{\hat{P}_{nj,t+1}}\right)^{1-\sigma}.$$

Import trade shares are

$$\hat{\pi}_{Fn,t+1}^{j} = \left(\frac{\hat{P}_{j,t+1}^{F}}{\hat{P}_{nj,t+1}}\right)^{1-\sigma}.$$

Exports are

$$\mathrm{EX}_{nj,t+1} = (\hat{c}_{nj,t+1})^{1-\sigma} \hat{D}_{j,t+1}^{F} \mathrm{EX}_{njt}.$$

The average wages of each region are

$$\hat{W}_{n,t+1} = \left(\sum_{j\in\mathcal{J}} \lambda_{njt} \hat{E}_{nj,t+1} \hat{W}_{nj,t+1}^{\theta}\right)^{\frac{1}{\theta}}.$$

Households' income is

$$\hat{I}_{n,t+1} = \frac{1+\iota_{t+1}}{1+\iota_t} \hat{W}_{n,t+1}.$$

Regional employment shares are

$$\hat{\lambda}_{nj,t+1} = \frac{\hat{E}_{nj,t+1} \hat{W}_{nj,t+1}^{\theta}}{\hat{W}_{n,t+1}^{\theta}}.$$

Sectoral labor supply is given by

$$\hat{H}_{nj,t+1} = (\hat{\lambda}_{nj,t+1})^{\frac{\theta-1}{\theta}} \hat{L}_{n,t+1}.$$

Goods market clearing is

$$\mathrm{GO}_{nj,t+1} = \sum_{m=1}^{N} \pi^{j}_{mn,t+1} \left[\sum_{k \in \mathcal{J}} \gamma^{j}_{k} \mathrm{GO}_{mk,t+1} + \alpha_j \big((1+\iota_{t+1}) \hat{W}_{n,t+1} \hat{L}_{n,t+1} W_{nt} L_{nt} \big) \right] + \mathrm{EX}_{nj,t+1}.$$

Labor market clearing is

$$W_{nj,t+1} H_{nj,t+1} = \gamma^{H}_{j} \mathrm{GO}_{nj,t+1}.$$

Dynamic equilibrium Define $u_{nt} = \exp(V_{nt})$, and $m_{nmt} = \exp(\tau_{nmt})$. Then, $\hat{u}_{n,t+1} = \exp(V_{n,t+1} - V_{nt})$, $\hat{m}_{nm,t+1} = \exp(\tau_{nm,t+1} - \tau_{nmt})$. Given initial allocation and an anticipated convergence sequence of changes in shocks, the following system of nonlinear equations is satisfied.

Migration shares are expressed as

$$\mu_{nm,t+1} = \frac{\mu_{nmt} (\hat{u}_{m,t+2})^{\frac{\beta}{\nu}} (\hat{m}_{nm,t+1})^{-\frac{1}{\nu}}}{\sum_{m'=1}^{N} \mu_{nm't} (\hat{u}_{m',t+2})^{\frac{\beta}{\nu}} (\hat{m}_{nm,t+1})^{-\frac{1}{\nu}}}. \tag{D.1}$$

The population evolves according to

$$L_{n,t+1} = \sum_{m=1}^{N} \mu_{mnt} L_{mt}. \tag{D.2}$$

Value functions are given by

$$\hat{u}_{n,t+1} = \left(\frac{\hat{I}_{nt}}{\hat{P}_{nt}} \right) \left(\sum_{m'=1}^{N} \mu_{nm't} (\hat{u}_{m',t+2})^{\frac{\beta}{\nu}} (\hat{b}_{m',t+1})^{\frac{1}{\nu}} (\hat{m}_{nm',t+1})^{-\frac{1}{\nu}} \right)^{\nu}. \tag{D.3}$$

Derivation of Eq. (D.1) and (D.3) I derive expressions in eq. (D.1) and (D.3). Migration shares can be expressed as

$$\begin{aligned} \mu_{nm,t+1} &= \frac{\exp(\beta V_{m,t+2} - \tau_{nm,t+1})^{\frac{1}{\nu}}}{\sum_{m'=1}^{N} \exp(\beta V_{m',t+2} - \tau_{nm',t+1})^{\frac{1}{\nu}}} \\ &= \frac{(\hat{u}_{m,t+2})^{\frac{\beta}{\nu}} (\hat{m}_{mn,t+1})^{-\frac{1}{\nu}} \exp(\beta V_{m,t+1} - \tau_{nmt})^{\frac{1}{\nu}}}{\sum_{m'=1}^{N} (\hat{u}_{m',t+2})^{\frac{\beta}{\nu}} (\hat{m}_{nm',t+1})^{-\frac{1}{\nu}} \exp(\beta V_{m',t+1} - \tau_{nm't})^{\frac{1}{\nu}}}. \end{aligned}$$

After dividing both the denominator and numerator of the above equation by $\sum_{m'=1}^{N} \exp(\beta V_{m',t+1} - \tau_{nm't})^{\frac{1}{\nu}}$, I can obtain the expression in eq. (D.1).

After taking eq. (4.9) in time differences, I obtain that

$$V_{n,t+1} - V_{n,t} = \ln \frac{I_{n,t+1}}{P_{n,t+1}} - \ln \frac{I_{nt}}{P_{nt}} + \nu \ln \frac{\sum_{m=1}^{N} \exp(\beta V_{m,t+2} - \tau_{nm,t+1})^{\frac{1}{\nu}}}{\sum_{m=1}^{N} \exp(\beta V_{m,t+1} - \tau_{nmt})^{\frac{1}{\nu}}}.$$

Taking exponential from both sides and using the expressions of $\hat{u}_{n,t+1}$ and $\mu_{nm,t+1}$, I can obtain the expression in eq. (D.3):

$$\hat{u}_{n,t+1} = \left(\frac{\hat{I}_{n,t+1}}{\hat{P}_{n,t+1}}\right)\left(\sum_{m=1}^{N} \mu_{nmt}(\hat{u}_{m,t+2})^{\frac{\beta}{\nu}}(\hat{m}_{nm,t+1})^{-\frac{1}{\nu}}\right)^{\nu}.$$

D.3 Algorithm

In this section, I describe the solution algorithm used to solve the model.

- Step 1. Given the path of the shocks $\{\hat{\mathbf{\Psi}}_t\}_{t=98}^{T}$ and $\{\hat{m}_{nmt}\}_{n=1,m=1,t=97}^{N,N,T}$, guess the path of $\{\hat{u}_{nt}^{(0)}\}_{n=1,t=98}^{N,T+1}$. The path converges at $T+1$, so set $\hat{u}_{n,T+1}^{(0)} = 1$, $\forall n \in \mathcal{N}$.

- Step 2. Given the initial allocation of migration shares $\{\mu_{nmt_0}\}_{n,m=1}^{N}$, using the guessed $\{\hat{u}_{nt}^{(0)}\}_{n=1,t=t_0+1}^{N,T+1}$, compute path of migration shares $\{\mu_{nmt}\}_{n,m=1,t=t_0+1}^{N,T+1}$ using eq. (D.1). Using the computed migration shares $\{\mu_{nmt}\}_{n,m=1,t=1}^{N,T+1}$, compute population for periods $t \geq t_0+1$ using eq. (D.2) and then, compute $\{\hat{L}_{nt}\}_{n=1,t=t_0}^{N,T}$.

- Step 3. For $t > t_0$, Using calculated $\{\hat{L}_{n,t+1}\}_{n=1}^{N}$, solve for $\{\hat{W}_{nj,t+1}\}_{n=1,j=1}^{N,J}$ that satisfy the system of equations of the static equilibrium in Section D.2 for each t.
    (a) Guess $\{\hat{W}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$ and $\{\hat{P}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$
    (b) Based on $\{\hat{W}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$, calculate the average wages $\{\hat{W}_{n,t+1}\}_{n=1}^{N}$ and regional employment shares $\{\hat{\lambda}_{nj,t+1}\}_{n=1,j=1}^{N,J}$. Then, iterate $\{\hat{P}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$ until convergence using the formulas for unit costs and price indices in Section D.2.
    (c) Check whether $\{\hat{W}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$ satisfy the labor market clearing condition. If not, go back to step (a).

- Step 4. For each t, solve backward for $\{\hat{u}_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$:

$$\hat{u}_{n,t+1}^{(1)} = \left(\frac{\hat{I}_{n,t+1}}{\hat{P}_{n,t+1}}\right)\left(\sum_{m=1}^{N} \mu_{nmt}(\hat{u}_{m,t+2}^{(0)})^{\frac{\beta}{\nu}}(\hat{m}_{nm,t+1})^{-\frac{1}{\nu}}\right)^{\nu}.$$

- Step 5. Take $\{(1-\omega)\hat{u}_{nt}^{(0)} + \omega \hat{u}_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$ for some weights $\omega \in (0,1]$, and return to Step 2. Continue until both $\{\hat{u}_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$ converge.

D.4 Calibration of Shocks and Initial Trade Shares

In this section, I describe the calibration procedure of the shocks, region-sector exports and import shares, and region-to-region trade shares of the initial period.

- Step 1. Let $\tilde{c}_{njt}$ denote for the unit cost of sector j in region n: $\tilde{c}_{njt} = c_{njt}/A_{njt}$. The static trade equilibrium of each period can be expressed as follows:

$$\mathrm{GO}_{njt} = (d^j_{nF}\tilde{c}_{njt})^{1-\sigma}D^F_{jt} + \sum_{m=1}^{N}\pi^j_{nmt}\Big[\sum_{k=1}^{J}\gamma^j_k\mathrm{GO}_{mkt} + \alpha_j\Big(\sum_{k'=1}^{J}(1+\iota_t)\gamma^H_{k'}\mathrm{GO}_{mk't}\Big)\Big],$$
$$\mathrm{IM}_{jt} = \sum_{n=1}^{N}\left[\pi^j_{Fnt}\Big[\sum_{k=1}^{J}\gamma^j_k\mathrm{GO}_{mkt} + \alpha_j\Big(\sum_{k'=1}^{J}(1+\iota_t)\gamma^H_{k'}\mathrm{GO}_{mk't}\Big)\Big]\right],$$
$$\mathrm{EX}_{jt} = \sum_{n=1}^{N}\mathrm{EX}_{njt},$$

  where

$$\pi^j_{mnt} = \frac{(d^j_{mn}\tilde{c}_{mjt})^{1-\sigma}}{\sum_{m'=1}^{N}(d^j_{m'n}\tilde{c}_{m'jt})^{1-\sigma} + (d^j_{nF}P^F_{jt})^{1-\sigma}}, \quad \pi^j_{Fnt} = \frac{(d^j_{Fn}P^F_{jt})^{1-\sigma}}{\sum_{m'=1}^{N}(d^j_{m'n}\tilde{c}_{m'jt})^{1-\sigma} + (d^j_{nF}P^F_{jt})^{1-\sigma}}, \tag{D.4}$$
$$\mathrm{EX}_{njt} = (d^j_{nF}\tilde{c}_{njt})^{1-\sigma}D^F_{jt}. \tag{D.5}$$

  Given the data on region-sector gross output, GO_{njt}, sectoral exports, EX_{jt}, sectoral imports, IM_{jt}, and the parametrized trade costs, d^j_{mn} and d^j_{Fn}, the above system of equations holds for each j and t. The above system of equation has $N+2$ number of equations with the same number of unknowns, $\{\tilde{c}_{njt}, P^F_{jt}, D^F_{jt}\}^{N,J}_{n=1,j=1}$, and the system of equation is exactly identified up to scale. Without loss of generality, I re-express P^F_{jt}. D^F_{jt}, and $\tilde{c}_{njt}$ relative to the unit cost of the reference region for each j and t: $\bar{c}_{njt} = \tilde{c}_{njt}/\tilde{c}_{n_0jt}$, $\bar{P}^F_{jt} = P^F_{jt}/\tilde{c}_{n_0jt}$, and $\bar{D}^F_{jt} = D^F_{jt}/\tilde{c}^{1-\sigma}_{n_0jt}$, where n_0 denotes the reference region. Then, I solve for $\bar{c}_{njt}$, $\bar{P}^F_{jt}$, and $\bar{D}^F_{jt}$ for each j and t upto normalization.

- Step 2. Using the backed-out $\{\bar{c}_{njt}, \bar{P}^F_{jt}, \bar{D}^F_{jt}\}^{N,J,02}_{n=1,j=1,t=98}$ for each sector and period, I can compute region-to-region trade shares and region-sector import shares from eq. (D.4) and regions-sector exports from eq. (D.5).

- Step 3. Once I back out $\{\bar{c}_{njt}, \bar{P}^F_{jt}, \bar{D}^F_{jt}\}^{N,J,02}_{n=1,j=1,t=98}$, region-sector price indices can be written as a function of the unit cost of the reference region, $\tilde{c}_{n_0jt}$:

$$P_{njt} = \left[\sum_{m=1}^{N}(d^j_{mn}\tilde{c}_{mjt})^{1-\sigma} + (d^j_{Fn}P^F_{jt})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = \tilde{c}_{n_0jt}\times\left[\sum_{m=1}^{N}(d^j_{mn}\bar{c}_{mjt})^{1-\sigma} + (d^j_{Fn}\bar{P}^F_{jt})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}.$$

Using the above expression, changes in region-sector price indices can be expressed as:

$$\hat{P}_{nj,t+1} = \hat{\bar{c}}_{n_0 j,t+1} \times \underbrace{\frac{\left[\sum_{m=1}^{N} (d^{j}_{mn}\bar{c}_{mj,t+1})^{1-\sigma} + (d^{j}_{Fn}\bar{P}^{F}_{j,t+1})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}{\left[\sum_{m=1}^{N} (d^{j}_{mn}\bar{c}_{mjt})^{1-\sigma} + (d^{j}_{Fn}\bar{P}^{F}_{jt})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}}_{\text{Obtained from the previous step}}.$$

Because I obtained $\bar{c}_{njt}$ and $\bar{P}^{F}_{jt}$ in level in the previous steps, the second term of the right-hand side is known. Therefore, once I pin down $\hat{\bar{c}}_{n_0 j,t+1}$, I can also pin down $\hat{P}_{nj,t+1}$.

I choose one reference sector j_0 and pin down $\hat{\bar{c}}_{n_0 jt}/\hat{\bar{c}}_{n_0 j_0 t}$ by fitting the PPI changes in the model relative to the reference sector $\widehat{PPI}_{jt}/\widehat{PPI}_{j_0 t}$ to the counterpart of the data (eq., 4.14).

- Step 4. Because I pin down $\hat{\bar{c}}_{n_0 jt}/\hat{\bar{c}}_{n_0 j_0 t}$ in the previous step, the remaining object is $\hat{\bar{c}}_{n_0 j_0 t}$. I pin down $\hat{\bar{c}}_{n_0 j_0 t}$ by fitting aggregate real GDP growth (eq., 4.15).

- Step 5. I compute changes in region-sector level unit costs, import costs, and foreign demand

$$\hat{c}_{nj,t+1} = \hat{\bar{c}}_{n_0 j,t+1} \times \hat{\bar{c}}_{nj,t+1}, \quad \hat{P}^{F}_{j,t+1} = \hat{\bar{c}}_{n_0 j,t+1} \times \hat{\bar{P}}^{F}_{jt}, \quad \text{and} \quad \hat{D}^{F}_{j,t+1} = \hat{\bar{c}}^{1-\sigma}_{n_0 j,t+1} \times \hat{\bar{D}}^{F}_{jt}.$$

  Note that I obtain $\hat{\bar{c}}_{n_0 j,t+1}$ from Steps 3 and 4, and $\hat{\bar{c}}_{nj,t+1}$, $\hat{\bar{P}}^{F}_{jt}$ and $\hat{\bar{D}}^{F}_{jt}$ from Step 1.

- Step 6. In this step, I calibrate productivity, amenity, and labor productivity shocks: $\{\hat{A}_{njt}, \hat{b}_{nt}, \hat{E}_{njt}\}_{n=1,j=1,t=98}^{N,J,T}$.

  Note that $\hat{\bar{c}}_{njt}$ is composed of changes in price of input bundles $\hat{c}_{njt}$ and productivity $\hat{A}_{njt}$. In order to back out $\hat{A}_{njt}$, I have to separately identify $\hat{c}_{njt}$ and $\hat{A}_{njt}$ from $\hat{\bar{c}}_{njt}$. To solve for $\hat{c}_{njt}$, I need to compute wages which require information of $\hat{E}_{njt}$ and population distribution that depends on $\hat{b}_{nt}$. These variables are determined in the dynamic equilibrium due to the perfect foresight of the agents. Therefore, I need to solve for the full dynamic model to back out these shocks.

  I use the following algorithm to back out $\{\hat{A}_{njt}, \hat{b}_{nt}, \hat{E}_{njt}\}_{n=1,j=1,t=98}^{N,J,T}$:

  A. Guess $\{\hat{A}^{(0)}_{njt}, \hat{b}^{(0)}_{nt}, \hat{E}^{(0)}_{njt}\}_{n=1,j=1,t=98}^{N,J,02}$

     (a) Based on the guess of $\{\hat{A}^{(0)}_{njt}\}_{n=1,j=1,t=98}^{N,J,02}$, set the future sequence of productivity shocks after 2003: $\hat{A}^{(0)}_{njt} = 1/\left(\prod_{\tau=98}^{02} \hat{A}^{(0)}_{nj\tau}\right)^{\frac{1}{25}}$, $\forall t \in \{03, \ldots, 28\}$ and $\hat{A}^{(0)}_{njt} = 1$, $\forall t \in \{29, \ldots, T\}$.

     (b) $\hat{b}^{(0)}_{nt} = \hat{E}^{(0)}_{njt} = 1$, $\forall n \in \mathcal{N}$, $\forall j \in \mathcal{J}$, $\forall t \in \{03, \ldots, T\}$

  B. Solve the model using the algorithm described in Section D.3.

C. Update a guess of $\{\hat{A}^{(0)}_{njt}\}^{N,J,02}_{n=1,j=1,t=98}$ based on the following steps.

   (a) Compare $\hat{c}^{(0)}_{njt}$ computed from the model based on the guess to $\hat{c}^{data}_{njt}$ obtained in the Step 5.

   (b) If $\hat{c}^{(0)}_{njt} > \hat{c}_{njt}$, compute a new guess of $\hat{A}^{(1)}_{njt}$ by decreasing $\hat{A}^{(0)}_{njt}$ and vice versa.

   (c) Use $\{\hat{A}^{(1)}_{njt}\}^{N,J,02}_{n=1,j=1,t=98}$ as a new guess and iterate steps B and C(a, b, c) until $|\hat{c}^{(0)}_{njt} - \hat{c}^{data}_{njt}| < \epsilon$, $\forall n \in \mathcal{N}$, $\forall j \in \mathcal{J}$, $\forall t \in \{98, \ldots, 02\}$ for some thresholds ϵ.

D. Update a guess of $\{\hat{E}^{(0)}_{njt}\}^{N,J,02}_{n=1,j=1,t=98}$ based on the following steps. Because $\hat{E}_{njt}$ is identified up to normalization within each region, I set $\hat{E}_{nj_0t} = 1$ for one reference sector j_0 across regions and periods.

   (a) Compare $\hat{\lambda}^{(0)}_{njt}$ computed from the model based on the guess to $\hat{\lambda}^{data}_{njt}$ obtained from the data (eq., 4.7).

   (b) If $\hat{\lambda}^{(0)}_{njt} > \hat{\lambda}_{njt}$, compute a new guess of $\hat{E}^{(1)}_{njt}$ by decreasing $\hat{E}^{(0)}_{njt}$ and vice versa.

   (c) Use $\{\hat{E}^{(1)}_{njt}\}^{N,J,02}_{n=1,j=1,t=98}$ as a new guess and iterate steps B, C(a, b, c), and D(a, b, c) until $|\hat{\lambda}^{(0)}_{njt} - \hat{\lambda}^{data}_{njt}| < \epsilon$, $\forall n \in \mathcal{N}$, $\forall j \in \mathcal{J}$, $\forall t \in \{98, \ldots, 02\}$ for some thresholds ϵ.

E. Update a guess of $\{\hat{b}^{(0)}_{nt}\}^{N,02}_{n=1,t=98}$ based on the following steps. Because $\hat{b}_{nt}$ is identified up to normalization, I normalize $\hat{b}_{n_0t} = 1$ for one reference region n_0.

   (a) Compare $L^{(0)}_{nt}$ computed from the model based on the guess to L^{data}_{nt} obtained from the data (eq., 4.11).

   (b) If $L^{(0)}_{nt} > L^{data}_{nt}$, then compute a new guess of $b^{(1)}_{nt}$ by decreasing $b^{(0)}_{nt}$ and vice versa.

   (c) Use $\{\hat{b}^{(1)}_{nt}\}^{N,02}_{n=1,t=98}$ as a new guess and iterate steps B, C(a, b, c), D(a, b, c) and E(a, b, c) until $|L^{(0)}_{nt} - L^{data}_{nt}| < \epsilon$, $\forall n \in \mathcal{N}$, $\forall t \in \{98, \ldots, 02\}$ for some thresholds ϵ.

F. Repeat steps A-E until convergence.

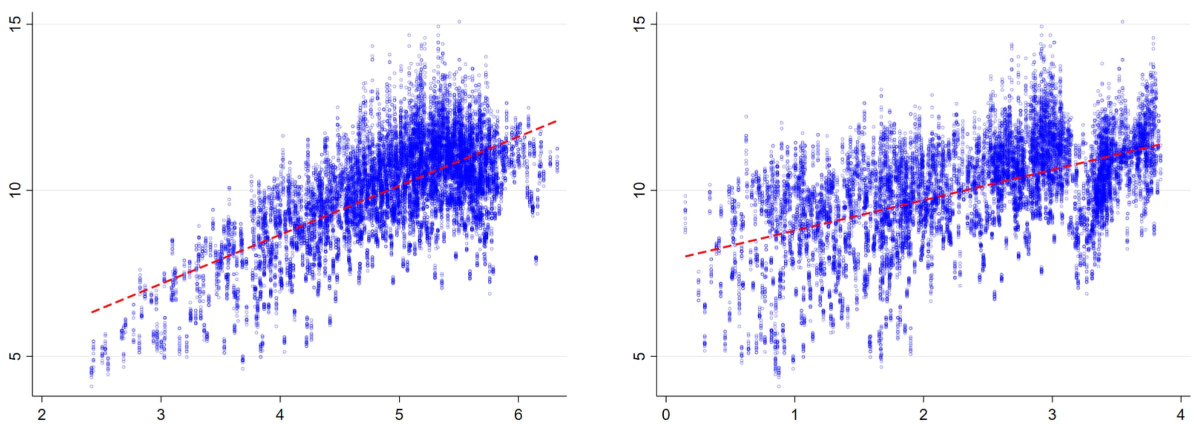
D.5 Correlates of the Inferred Migration Frictions

I construct an index of regional conflicts by computing regional dissimilarity in candidates' shares of the vote in the 1992 14th presidential election, which is a good proxy for cultural, economic, and political conflicts between two regions based on the institutional details of South Korea. The index is constructed using each candidate's shares of the vote. I compute the index between regions m and n as

$$\text{Index}_{nm} = 100 \times \sqrt{\frac{\sum_c (\pi^c_n - \pi^c_m)}{\text{The Number of Candidates}}},$$

where π^c_n is candidate c's share of votes of region n and the denominator is the number of candidates in the election. The southwestern regions had been culturally, economically, and politically discriminated against since the 1970s. In the 1970s and 1980s, the authoritarian government pursued an unequal development strategy by heavily investing in manufacturing sectors in the southeastern regions (Choi and Levchenko, 2023). Moreover, hundreds of people were massacred in 1980 during the popular uprising that happened in the southwestern regions against the authoritarian regime for democratic freedom. The unequal development strategy and the massacre led to political regionalism. Since the political system became democratized in 1987, people living in the southwestern regions tended to vote for the candidate from the opposition party and against the authoritarian regime, whereas those living in the southeastern regions tended to vote for the ruling party that inherited the legacy of the authoritarian regime.

Figure D11. Correlates of the Inferred Migration Frictions



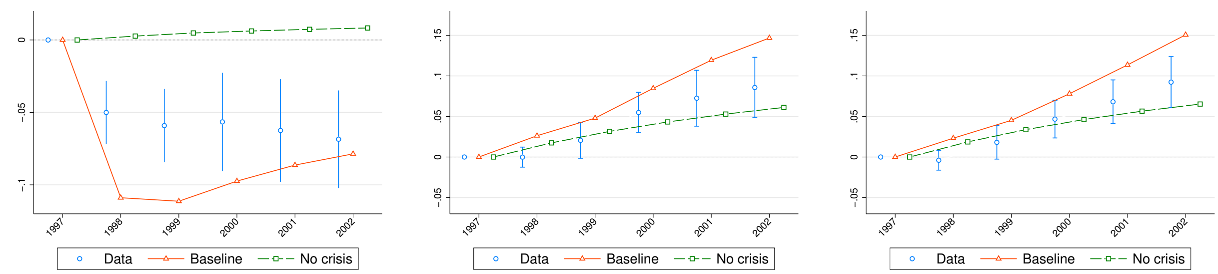
A. Log distance

B. Index for regional conflicts

Notes. Panels A and B are the scatter plots between the inferred migration frictions and log distance and between such frictions and the index for regional conflicts. The red dashed lines are the corresponding linear fits.

D.6 Additional Figures and Tables

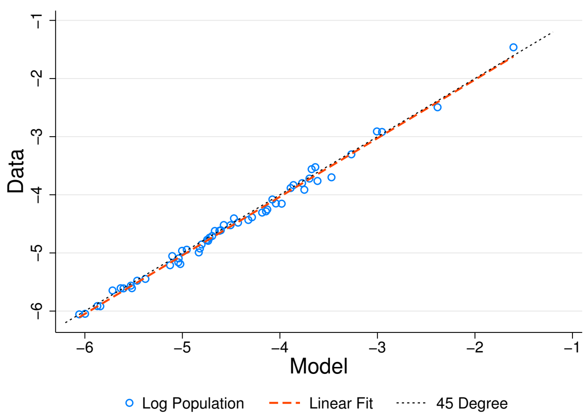
Figure D12. Robustness. Non-Targeted Moments. Other Variables. Migration, Employment, and the Crisis



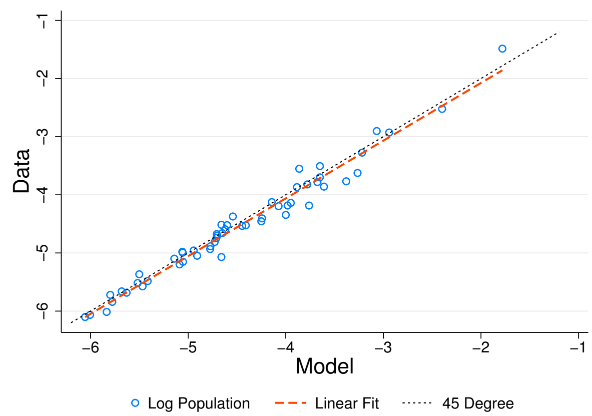
A. Migration outflow B. Total emp. C. Non-top 5 emp.

Notes. The figure the estimated event study coefficients when turning off a set of specified shocks at a time. The blue circle represents the estimated event study coefficients from the data, with the 95% confidence intervals (Figures 2 and 3).

Figure D13. Non-Targeted Moments. Population Distributions



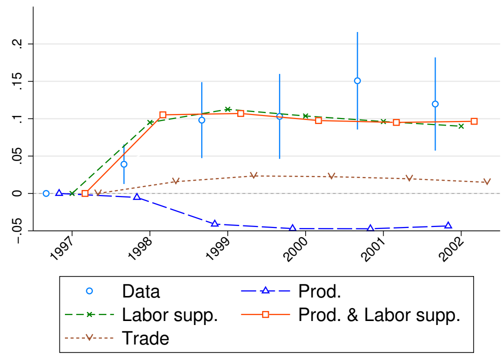
A. Population 2000



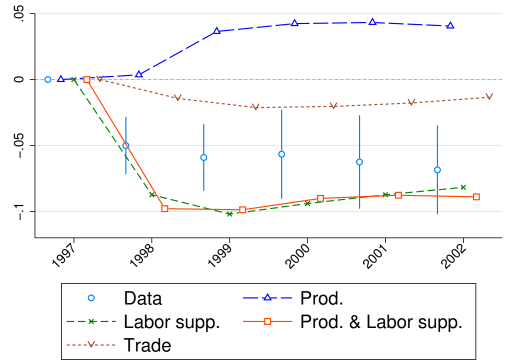
B. Population 2002

Notes. Panels A and B present population distribution in 2000 and 2002 from the model and the data, respectively. Total population is normalized to 1. The estimated coefficient for the linear fit is 1.01 and 1, with adjusted R-squared of 0.99 and 0.97, respectively.

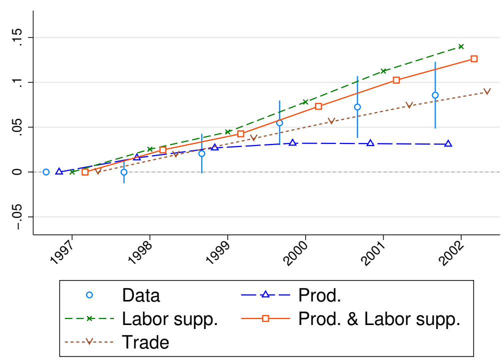
Figure D14. Robustness. Feeding Only Specified Shocks. The Role of Individual Shocks



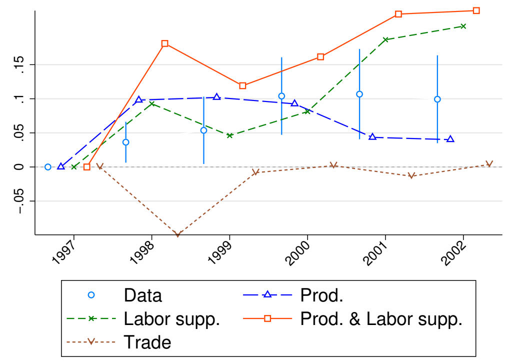
A. Migration inflow



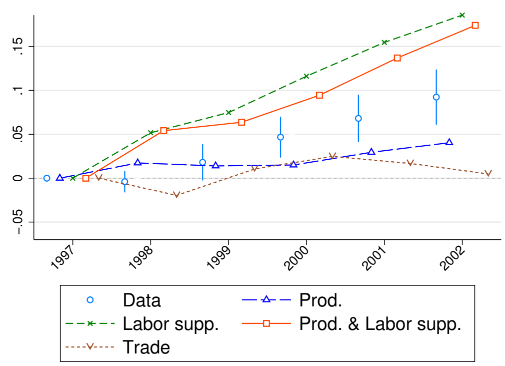
B. Migration outflow



C. Total emp.



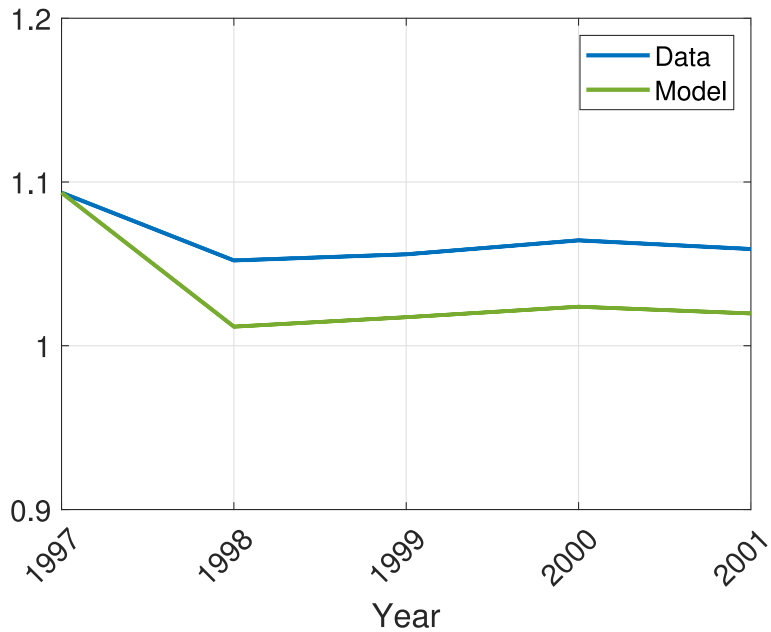
Top 5 emp.



Non-top 5 emp

Notes. The figure the estimated event study coefficients when feeding in only a set of specified shocks at a time. The blue circle represents the estimated event study coefficients from the data, with the 95% confidence intervals (Figures 2 and 3).

Figure D15. Non-Targeted Moment. Capital Accumulation. Data vs. Model



Growth in the Aggregate Capital Stock (%)

Notes. The figure plots growth in the aggregate real capital stock of the data and model, respectively.

E Model Extension

E.1 Unemployment

Downward Nominal Rigidity Following Rodriguez-Clare et al. (2022), I introduce downward nominal rigidity (DWNR) at the region-sector level:

$$W_{njt} \geq \delta_{nj} W_{nj,t-1}, \qquad \delta_{nj} \geq 0.$$

δ_{nj} is a region-sector specific parameter, with a higher value corresponding to tighter degree of the rigidity. $\delta = 0$ implies no DWNR. The DWNR leads to unemployment, an employment level below labor supply in efficiency unit:

$$H_{njt} \leq \tilde{H}_{njt}, \tag{E.1}$$

where H_{njt} is amount of employed effective labor and $\tilde{H}_{njt}$ is the total effective labor supply. $e_{njt} = H_{njt}/\tilde{H}_{njt}$ is employment rate of effective labor. When households allocate their workers in sector j, they not only consider nominal wages W_{njt} but also employment rate e_{njt}.

Region n households' allocate worker h to sector j only if sector j generates the highest labor income adjusted for unemployment rates, over other sector: $\epsilon^h_{njt} \in \Omega_{njt}$, where $\Omega_{njt} = \{\boldsymbol{\epsilon}_t | W_{njt} e_{njt} \epsilon_{njt} \geq W_{nkt} u_{nkt} \epsilon_{nkt}, \forall k \in \mathcal{J}\}$. To simplify the analysis, I assume that sum of wages generated in region-sector nj is equally distributed to all workers allocated to nj. Shares of workers allocated to sector j in region n are expressed as

$$\lambda_{njt} = \frac{(e_{njt} W_{njt})^{\theta}}{\sum_k (e_{nkt} W_{nkt})^{\theta}}. \tag{E.2}$$

The total labor income of region n's household is

$$W_{nt} = \Big[\sum_{j=1}^{J} (W_{njt} e_{njt})^{\theta}\Big]^{\frac{1}{\theta}}.$$

Total labor supply is given as

$$\tilde{H}_{njt} = L_{nt} \int_0^1 \left[\int_{\Omega_{njt}} \epsilon^h_{njt} dF(\boldsymbol{\epsilon}^h_t)\right] \mathrm{d}h = \Gamma^1 \lambda_{njt}^{\frac{\theta-1}{\theta}} L_{nt}.$$

Market clearing I introduce a nominal anchor that prevents nominal wages from rising so much and making the DWNR constraints non-binding every period. Following Rodriguez-Clare et al. (2022), I assume that the nominal GDP of South Korea grows at a constant rate of φ:

$$\sum_{n=1}^{N} \sum_{j=1}^{J} W_{njt} H_{njt} = \varphi \sum_{n=1}^{N} \sum_{j=1}^{J} W_{nj,t-1} H_{nj,t-1}. \tag{E.3}$$

Labor market clearing conditions satisfy

$$W_{njt}H_{njt} = \gamma_j^H \mathrm{GO}_{njt}$$

and complementary slackness that combines eq. (E.1) and (E.1)

$$(\tilde{H}_{njt} - H_{njt})(W_{njt} - \delta_{nj}W_{nj,t-1}) = 0.$$

Other equilibrium conditions and variables are expressed are in the same to those of the baseline model in the main text.

E.1.1 Discussion

The employment rate e_{njt}^{θ} in eq. (E.2) to labor supply shocks in E_{njt} in eq. (4.7).

E.2 Intertemporal Investment in Capital

In this section, following Kleinman et al. (2021), I extend the model to incorporate dynamic investment in capital. I introduce new agents, landlords, who are immobile across regions. Landlords in each region can produce one unit of capital using one unit of final goods. They choose their consumption and investment to maximize their intertemporal utility:

$$\nu_{nt}^k = \sum_{s=t_0}^{\infty} \beta^{t+s} \frac{(C_{n,t+s}^k)^{1-1/\psi}}{1-1/\psi}, \tag{E.4}$$

subject to the budget constraint $r_{nt}K_{nt} = P_{nt}(C_{nt}^k + K_{n,t+1} - (1-\delta)K_{nt})$, where r_{nt} is the rental rate of capital. $r_{nt}K_{nt}$ is the total income from the existing capital stock, $P_{nt}C_{nt}^k$ is the total value of their consumption, and $P_{nt}(K_{n,t+1} - (1-\delta)K_{nt})$ is the total value of their investment.

Capital is an input to production and production function is given as

$$q_{njt} = A_{njt} H_{njt}^{\gamma_j^H} K_{njt}^{\gamma_j^K} \prod_{k=1}^{J} (M_{njt}^k)^{\gamma_j^k}, \qquad \gamma_j^H + \gamma_j^K + \sum_k \gamma_j^k = 1.$$

Capital stock is freely mobile across sectors within regions, but immobile across regions, which is interpreted as physical structure such as factories.

Their optimal investment decisions are characterized by the following law of motion for capital:

$$K_{n,t+1} = (1-\zeta_{nt})R_{nt}K_{nt}, \tag{E.5}$$

where $R_{nt} = 1 - \delta + r_{nt}/P_{nt}$ is the gross return on capital and ζ_{nt} is recursively defined as

$$\zeta_{nt}^{-1} = 1 + \beta^{\psi}\left(R_{n,t+1}^{\frac{\psi-1}{\psi}} \zeta_{n,t+1}^{-\frac{1}{\psi}}\right)^{\psi}.$$

Landlords save the fraction of $(1-\zeta_{nt})$ out of current-period wealth $R_{nt}K_{nt}$. The optimal consumption of region n's landlords satisfies $C^k_{nt} = \zeta_{nt}R_{nt}K_{nt}$. Capital stock, as well as population, is a state variable.

Capital market clearing requires that landlords' capital income equal rental payments for its use. Cost-minimization of intermediate goods producers and the zero profit condition imply that the capital market clearing condition is

$$r_{nt} = \frac{\sum_{j=1}^{J}(\gamma^K_j/\gamma^H_j)W_{njt}H_{njt}}{K_{nt}}. \tag{E.6}$$

Capital market clearing implies that capital evolves according to

$$K_{nj,t+1} = \left(\frac{(\gamma^K_j/\gamma^H_j)\hat{W}_{nj,t+1}\hat{H}_{nj,t+1}W_{njt}H_{njt}}{\sum_{k\in\mathcal{J}}(\gamma^K_k/\gamma^H_k)\hat{W}_{nk,t+1}\hat{H}_{nk,t+1}W_{nkt}H_{nkt}}\right)K_{n,t+1}$$

The equilibrium with capital accumulation is defined as follows.

Definition 2. *Given the parameters of the model, $\{\boldsymbol{\Psi}_t\}_{t=t_0}^{\infty}$, $\{\boldsymbol{\tau}_t\}_{t=t_0}^{\infty}$, and initial allocations of the state variables $\{L_{nt_0}, K_{nt_0}\}_{n=1}^{N}$, the competitive equilibrium of the model is the set of population, sectoral allocation of workers, wages, expected lifetime utilities, rental rate of capital, and capital stock $\{L_{nt},\ \lambda_{njt},\ W_{njt},\ V_{nt},\ r_{nt},\ K_{n,t+1}\}_{n=1,j=1,t=t_0}^{N,J,\infty}$ that satisfies the following condition for each region n, each sector j, and all periods t: (i) Given $\{W_{njt}\}_{n=1,j=1}^{N,J}$, households optimally allocate their workers across different sectors (eq., 4.7); (ii) $\{V_{nt}\}_{n=1}^{N}$ satisfies eq. (4.9); (iii) $\{L_{nt}\}_{n=1}^{N}$ evolves according to eq. (4.11); (iv) $\{K_{n,t+1}\}_{n=1}^{N}$ evolves according to eq. (E.5); and (v) goods, labor, and capital market clearing conditions are satisfied (eq., 4.12, 4.13, E.6).*

With the additional data on region-sector capital stock, I use the following algorithm for solving the model.

- Step 1. Given the path of the shocks $\{\hat{\boldsymbol{\Psi}}_t\}_{t=t_0}^{T}$ and $\{\hat{\boldsymbol{\tau}}^c_t\}_{t=t_0}^{T}$, guess the path of $\{\hat{u}^{(0)}_{nt}\}_{n=1,t=t_0+1}^{N,T+1}$ and $\{\zeta^{(0)}_{nt}\}_{n=1,t=t_0+1}^{N,T+1}$. The path converges at $T+1$, so set $\hat{u}^{(0)}_{n,T+1} = 1$, $\forall n \in \mathcal{N}$.
- Step 2. Based on the guessed consumption rates and the observed allocation of capital $\{K_{nt_0}\}_{n=1}^{N}$ and $\{K_{n,t_0+1}\}_{n=1}^{N}$, set the gross return of capital at time t_0+1 as follows:

$$R_{n,t_0+1} = \frac{K_{n,t_0+1}}{K_{nt_0}}(1-\zeta^{(0)}_{nt_0}).$$

- Step 3. Given the initial allocation of migration shares $\{\mu_{nmt_0}\}_{n,m=1}^{N}$, using the guessed $\{\hat{u}^{(0)}_{nt}\}_{n=1,t=t_0+1}^{N,T+1}$, compute path of migration shares $\{\mu_{nmt}\}_{n,m=1,t=t_0+1}^{N,T+1}$:

$$\mu_{nm,t+1} = \frac{\mu_{nmt}(\hat{u}_{m,t+2})^{\frac{\beta}{\nu}}(\hat{m}_{nm,t+1})^{\frac{1}{\nu}}}{\sum_{m'\in\mathcal{N}} \mu_{nm't}(\hat{u}_{m',t+2})^{\frac{\beta}{\nu}}(\hat{m}_{nm',t+1})^{\frac{1}{\nu}}}.$$

Using the computed migration shares $\{\mu_{nmt}\}_{n,m=1,t=1}^{N,T+1}$, compute population for periods $t \geq t_0 + 1$:

$$L_{n,t+1} = \sum_{m=1}^{N} \mu_{mnt} L_{mt}.$$

and calculate $\{\hat{L}_{nt}\}_{n=1,t=t_0}^{N,T}$.

- Step 4. For $t > t_0$,
  1. Using calculated $\{\hat{L}_{n,t+1}\}_{n=1}^{N}$ and $\{\hat{K}_{n,t+1}\}_{n=1}^{N}$, solve for $\{\hat{W}_{nj,t+1}\}_{n=1,j=1}^{N,J}$ that satisfy the system of equations of the static equilibrium in Section D.2 for each t.
     (a) Guess $\{\hat{W}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$ and $\{\hat{P}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$
     (b) Based on $\{\hat{W}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$, calculate the average wages $\{\hat{W}_{n,t+1}\}_{n=1}^{N}$ and regional employment shares $\{\hat{\lambda}_{nj,t+1}\}_{n=1,j=1}^{N,J}$. Then, iterate $\{\hat{P}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$ until convergence using the formulas for unit costs and price indices in Section D.2.
     (c) Check whether $\{\hat{W}_{nj,t+1}^{(0)}\}_{n=1,j=1}^{N,J}$ satisfy the labor market clearing condition. If not, go back to step (a).
  2. Compute the next period gross return on capital $\{R_{n,t+1}\}_{n=1}^{N}$[35]:

$$R_{n,t+1} = (1-\delta) + \frac{\hat{W}_{nj,t+1}\hat{H}_{nj,t+1}}{\hat{P}_{n,t+1}\hat{K}_{nj,t+1}}(R_{nt} - (1-\delta)).$$

     Because of cost minimization, the above expression holds for any $j \in \mathcal{J}$.
  3. Using the next period gross return on capital $\{R_{n,t+1}\}_{n=1}^{N}$ and guessed $\{\zeta_{n,t+1}^{(0)}\}_{n=1}^{N}$, compute capital $\{K_{n,t+2}\}_{n=1}^{N}$ in period $t+2$:

$$K_{n,t+2} = (1 - \zeta_{n,t+1}^{(0)}) R_{n,t+1} K_{n,t+1}.$$

[35]Because $R_{n,t+1} = (1-\delta) + \frac{r_{n,t+1}}{P_{n,t+1}}$, $\frac{R_{n,t+1}-(1-\delta)}{R_{nt}-(1-\delta)} = \frac{\hat{r}_{n,t+1}}{\hat{P}_{n,t+1}}$ holds. The cost minimization implies that $\frac{\hat{W}_{nj,t+1}\hat{H}_{nj,t+1}}{\hat{r}_{n,t+1}\hat{K}_{nj,t+1}} = 1$, $\forall j \in \mathcal{J}$. Substituting $\hat{r}_{n,t+1}$ by $\hat{W}_{nj,t+1}\hat{H}_{nj,t+1}/\hat{K}_{nj,t+1}$ in $\frac{R_{n,t+1}-(1-\delta)}{R_{nt}-(1-\delta)} = \frac{\hat{r}_{n,t+1}}{\hat{P}_{n,t+1}}$, we can obtain that $R_{n,t+1} = (1-\delta) + \frac{\hat{W}_{nj,t+1}\hat{H}_{nj,t+1}}{\hat{P}_{n,t+1}\hat{K}_{nj,t+1}}(R_{nt} - (1-\delta))$.

- Step 5. For each t, solve backward for $\{\hat{u}_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$:

$$\hat{u}_{n,t+1}^{(1)} = \left(\frac{\hat{I}_{n,t+1}}{\hat{P}_{n,t+1}}\right)\left(\sum_{m=1}^{N} \mu_{nmt}(\hat{u}_{m,t+2}^{(0)})^{\frac{\beta}{\nu}}(\hat{m}_{nm,t+1})^{-\frac{1}{\nu}}\right)^{\nu}.$$

- Step 6. For each t, solve backward for $\{\zeta_{nt}^{(1)}\}_{n=1,t=1}^{N,T+1}$:

$$\zeta_{nt}^{(1)} = \frac{\zeta_{n,t+1}^{(0)}}{\zeta_{n,t+1}^{(0)} + \beta^{\psi} R_{n,t+1}^{\psi-1}},$$

where $R_{n,T+1} = 1/\beta$ is imposed.

- Step 7. Take $\{(1-\omega)\hat{u}_{nt}^{(0)} + \omega\hat{u}_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$ and $\{(1-\omega)\zeta_{nt}^{(0)} + \omega\zeta_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$ for some weights $\omega \in (0,1]$, and return to Step 2. Continue until both $\{\hat{u}_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$ and $\{\zeta_{nt}^{(1)}\}_{n=1,t=t_0+1}^{N,T+1}$ converge.