The China Shock and Internal Migration: Evidence from Bilateral Migration Flows*

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Abstract

Using Korean administrative data spanning nearly two decades and covering the universe of bilateral migration flows across local labor markets, we examine how the China trade shock shapes internal migration. While prior studies rely on net population changes to measure labor adjustment, we exploit bilateral migration flows that separately capture in- and out-migration. We find that trade exposure primarily increases out-migration from adversely affected regions, with limited effects on in-migration, revealing asymmetric spatial adjustment. Decomposing the shock, export expansion reduces out-migration, whereas import competition increases it. Migration responses are strongest among prime working-age individuals and substantially weaker among younger and older cohorts. Single-person households are more responsive than multi-person households. Overall, bilateral data reveal substantial migration responses that conventional net population measures fail to detect, offering new insight into the "missing migration puzzle."

Keywords: China trade shock, Labor adjustment, Internal migration, Korea
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1 Introduction

Recently, much attention has been paid to internal migration responses to trade liberalization, particularly a puzzling phenomenon known as the "missing migration puzzle," referring to the empirical finding that workers in trade-exposed regions display limited geographic mobility despite significant local labor-market disruptions (Balsvik, Jensen, and Salvanes 2015; Dix-Carneiro and Kovak 2019; Twinam 2022; Autor, Dorn, and Hanson 2021; Borusyak, Dix-Carneiro, and Kovak 2022). Many economists have confirmed that "gains from trade" do not ensure an even distribution of the benefits arising from trade liberalization. Increased trade can offer some firms and industries broader export markets and lower prices for intermediate goods. However, trade can also generate new challenges, as it can harm domestic industries with comparative disadvantages and their workers. Previous studies on trade liberalization have highlighted such disparate impacts of trade shocks across regions. Specifically, they have shown that regions facing more intense import competition suffer more severe adverse effects from trade liberalization (e.g., Autor, Dorn, and Hanson 2013).

Given the spatial disparities between winners and losers arising from trade liberalization, migration naturally emerges as a potential response to trade shocks. To adjust to such shocks in local labor markets, one would expect workers to migrate from declining to more prosperous regions. However, numerous studies attempting to document this pattern have found inconclusive or null results. Several studies in Brazil, Europe, and the United States have indicated only a limited migration response to trade shocks (Autor, Dorn, and Hanson 2013; Balsvik, Jensen, and Salvanes 2015; Monras 2020; Donoso, Martín, and Minondo 2015; Dix-Carneiro and Kovak 2019), while more recent work has detected potential migration responses to trade shocks (Greenland, Lopresti, and McHenry 2019; Twinam 2022).

To further complicate matters, owing to data limitations, most of the aforementioned studies relied on net population changes in regions to examine labor adjustment to trade shocks. As a result, they may not have been able to comprehensively assess the impact of trade shocks on migration. While net population changes offer an indirect way to gauge internal migration, this measure does not fully capture gross migration flows, as it fails to separate in-migration from out-migration. For example, net population change will be zero if the magnitude of in-migration equals that of out-migration. Thus, even significant migration flows may go undetected when one examines net population changes alone.[1] Due to these various difficulties, the issue we refer to as the "missing migration puzzle" remains an open question in the international trade literature.

In this paper, we aim to address the "missing migration puzzle" using unique data on bilateral migration flows from Korea. Starting as far back as 1996, South Korea has doc-

1. Net population changes also reflect births and deaths, which further complicates the measurement of actual migration flows.

umented annual internal migration for its entire population.[2] Notable advantages of the dataset are that (i) it records bilateral migration flows at the household level for all of South Korea, (ii) it documents household moves between detailed geographical units (down to regions with an average population of 20,000), and (iii) it includes basic demographics (e.g., age group and household size) for all household members as well as their reason for migration. This highly detailed dataset on internal migration enables us to directly measure the impact of regional trade shocks on internal migration.

By leveraging these detailed micro-level administrative data on bilateral migration, we uncover several novel findings regarding the causal impact of the China trade shock on bilateral migration flows. First and foremost, we find that origin trade shocks are the primary driver of bilateral migration responses to the China shock. Import competition in the origin commuting zone significantly increases out-migration from affected regions, while export expansion in the origin retains workers by reducing out-migration. In contrast, trade shocks in the destination commuting zone play a comparatively limited role. This finding offers a new perspective on the missing migration puzzle: prior studies predominantly relied on net population changes, which capture only the combined effect of in- and out-migration, and may therefore have failed to detect meaningful mobility responses. By decomposing bilateral migration flows into their origin and destination components, our approach separately identifies the push effect of import competition driving out-migration and the pull effect of destination export opportunities attracting in-migration, both of which are obscured in aggregate net population analyses.

Our analysis further reveals that the migration response exhibits significant heterogeneity across demographic groups and household configurations. We discover that the mobility response is primarily driven by prime-age workers (aged 35–54), while younger cohorts and those approaching retirement age show significantly less sensitivity to trade exposure. This result seems to be in line with Pierce and Schott (2020) where they find that the effects of China trade shock were present primarily among working-age whites. We also find that migration responses to the trade shock are strongly influenced by household structure. Specifically, we find that single-person households are more responsive to trade shocks than multi-person households.

Our paper is related to several strands of literature on trade liberalization and its impact on local labor markets and migration patterns. A first strand examines trade shocks and migration outside the China shock context. Hanlon (2017) analyzed the effect of a transitory shock in the British textile sector caused by the U.S. Civil War, and Dix-Carneiro and Kovak (2019) studied the effect of trade liberalization in Brazil; neither study provided strong

2. As of 2023, yearly migration flow data are available through 2022. Beginning in 2001, the dataset provides more detailed information on bilateral migration flows.

evidence of substantial mobility responses to the onset of trade shocks. However, Twinam (2022) used the quartz crisis in Switzerland to show that a trade shock led to a rapid loss of population (i.e., out-migration), demonstrating that larger migration responses can emerge under certain conditions. While he did find larger migration responses to the trade shock, our approach differs in several dimensions: (i) we use actual bilateral migration flows rather than population changes; (ii) while he focused on import competition, we examine both import and export shocks originating from the China trade shock; and (iii) we study entire regions using bilateral flow data, while his research focused primarily on a single region.

A second, and more directly related, strand examines the impact of the China trade shock on migration. In the U.S. context, Autor, Dorn, and Hanson (2013) found that the significant increase in imports from 1990 to 2007 adversely affected both employment and wages in areas susceptible to competition from China, yet this did not result in a notable decrease in population in these regions, suggesting that the geographic mobility of affected workers may have been limited. Subsequent work has partially revised this conclusion. Greenland, Lopresti, and McHenry (2019) found that the China shock did result in decreased growth rates in affected areas, though this decline manifested with a notable lag. More recently, Autor, Dorn, and Hanson (2023) found that U.S. commuting zones with greater exposure to the China trade shock experienced significant net decreases in the population of foreign-born workers. Our approach differs from theirs in that we use novel bilateral migration flows rather than population changes to capture workers' mobility responses. We also find significant mobility patterns among native workers, which were not found in Autor, Dorn, and Hanson (2023). Additionally, Facchini et al. (2019) analyzed the impact of China's integration into the world economy on internal migration in mainland China. While this study identified a notable increase in internal in-migration due to reduced regional trade policy uncertainty, its scope is limited by China's stringent policies on individual internal migration decisions, known as the "Hukou system." Our research benefits from studying a context in which no such restrictions on internal migration decisions exist.

In Europe, initial studies similarly found limited mobility responses: Balsvik, Jensen, and Salvanes (2015) and Donoso, Martín, and Minondo (2015) examined the effect of the China shock on Norway and Spain, respectively, but both reported only modest effects. Our study significantly enriches this literature by leveraging unique administrative data from Korea to pinpoint the previously unidentified mobility response to the China shock. Using bilateral migration data encompassing the entire population, our findings suggest that the perceived absence of a mobility response in the previous literature may stem from the reliance on net population measures, which capture only the combined effect of in- and out-migration, rather than from a genuine lack of worker mobility. By separately identifying the origin push and destination pull channels through which trade shocks operate, our bilateral approach uncovers migration responses that net measures inherently obscure.

Our paper is most closely related to Monras (2020) and Borusyak, Dix-Carneiro, and Kovak (2022). Monras (2020) documents that in-migration rates respond more strongly than out-migration rates to economic shocks, using local labor demand shocks induced by the Great Recession. Our paper complements their analysis in that, unlike the American Community Survey and the CPS data used in their study—which rely on relatively limited sample sizes—we use bilateral migration data that record movements for the entire population of South Korea. In addition, we incorporate local shocks at both the origin and the destination and model the full dynamics of in- and out-migration within a single specification, allowing us to jointly assess their impacts and dynamic responses. Finally, by using data spanning two decades, we capture longer-run migration responses to local economic shocks. Borusyak, Dix-Carneiro, and Kovak (2022) introduce the bilateral nature of location choices in migration to more accurately assess the effect of trade shocks on labor adjustment. Using a model of local labor markets with mobility costs and the census of the Brazilian formal labor market (RAIS data), they show that past conclusions on migration can be misleading due to this bilateral nature of migration. Our paper is complementary to theirs in that our bilateral migration data record movements for the entire population, unlike the RAIS data, which cover only employed workers in the formal sector. By providing movement records for the entire population, we can also account for employees in the informal sector and unemployed individuals. Additionally, we extend their research by providing detailed information on the demographics and family structure of moving individuals. Borusyak, Dix-Carneiro, and Kovak (2022) model workers' location choices using data on mobility costs across industries and locations. As our data are collected at the household level and provide basic demographics (age and household size) for household members, we can introduce a new channel of mobility costs associated with age and family structure.

Our paper is also related to studies examining the impact of trade shocks in the context of South Korea. Kim (2006) and Choi and Kim (2015) found that trade growth with China positively influenced employment in Korea. On the other hand, Koo and Whang (2018), focusing solely on the manufacturing sector, show that while the China shock led to job losses, it simultaneously catalyzed job creation, thereby offsetting the overall impact. Our paper extends this strand of literature by examining the impact of the China trade shock on mobility responses in South Korea.

The rest of the paper is organized as follows. Section 2 describes the data and constructs the exposure to trade shocks. Section 3 discusses our empirical specification. Section 4 presents our baseline results and robustness checks. Section 5 examines the heterogeneous effects of trade shocks by age and household size, and explores possible explanations for these varied impacts. Finally, Section 6 concludes.

2 Data

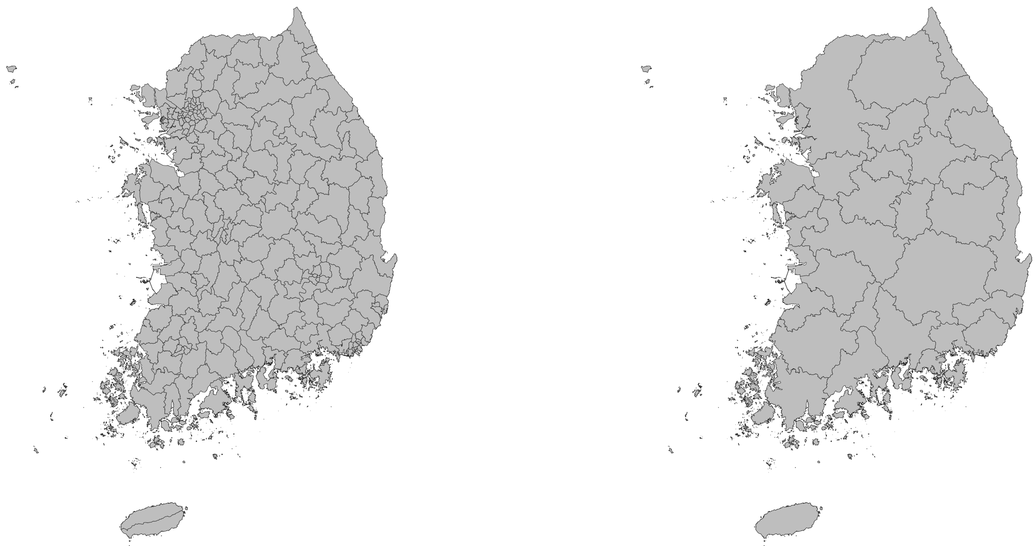
2.1 Migration Data

Our primary dataset is the Internal Migration Data provided by Statistics Korea, which comprises administrative records of all bilateral migrations within South Korea. As mandated by law (Article 16 of the Resident Registration Act), Korean residents are required to report a change of residence to the local authorities within 14 days of relocation. This dataset is provided at the household level and contains information on the age and gender of each household member, as well as the primary reason for migration. We aggregate these household-level data to construct bilateral migration flows across "si-gun-gu" administrative units, which we refer to as "districts" throughout the paper. While the dataset offers location information at an even finer unit called "dong," we use "si-gun-gu" as our primary unit of analysis because it is analogous to a county in the U.S. context. Although its average population size is approximately 20,000, roughly twice as large as that of a U.S. county, both geographic units represent the smallest administrative divisions responsible for essential government services such as education, fire protection, and policing. We use these 225 districts for our migration analysis, while exposure to trade shocks is calculated at the local labor market level.[3] To maintain consistency with commuting zones in the U.S., we employ the concept of Travel-to-Working Areas developed by Lee and Lee (2015), who establish commuting zones in Korea based on commuting flows. Following their methodology, South Korean districts are grouped into 33 regions. Figures 1(a) and 1(b) show the map of South Korea, delineating its districts and commuting zones, respectively.

2.2 Trade Data

We use the UN Comtrade Database on South Korean imports and exports at the 6-digit Harmonized System (HS) product level to construct trade shock measures based on imports from China to South Korea and exports from South Korea to China. We use annual imports from and exports to China for the years 2001, 2010, and 2019 to construct changes in trade volume. Table 1 shows the value of Korean imports from China and exports to China for the years 2001, 2010, and 2019. This table illustrates a significant surge in trade volume between South Korea and China from 2001 to 2010, followed by a period of relative stability after 2010. Notably, South Korea sustained a positive trade balance after 2000, with exports growing more rapidly than imports. This suggests that the export channel may have been

3. The total number of districts can differ annually due to changes in administrative divisions. We minimize this discrepancy by retaining most of the cities that were present throughout the period from 2001 to 2020. We also exclude one district that consists solely of remote islands (Ulleung County). The detailed procedure is described in Appendix E.



(a) Districts (b) Commuting Zones

Figure 1: Map of South Korea

Notes: The figures display the districts ("si-gun-gu") and commuting zones of South Korea, respectively. In total, there are 225 districts and 33 commuting zones.

important in shaping regional labor allocation.

Table 1: Value of Trade for Korea (1990, 2001, 2010, 2019)

Trade with China (in billion USD)			
Year	Export	Import	Balance
1990	2.4	2.6	-0.2
2001	25.4	18.6	6.8
2010	135.6	83.1	52.5
2019	136.2	107.2	29.0

Notes: All values of exports and imports are from the Comtrade dataset. All values are in billions of USD, adjusted to 2019 dollars.

2.3 Measuring Exposure to Trade Shocks

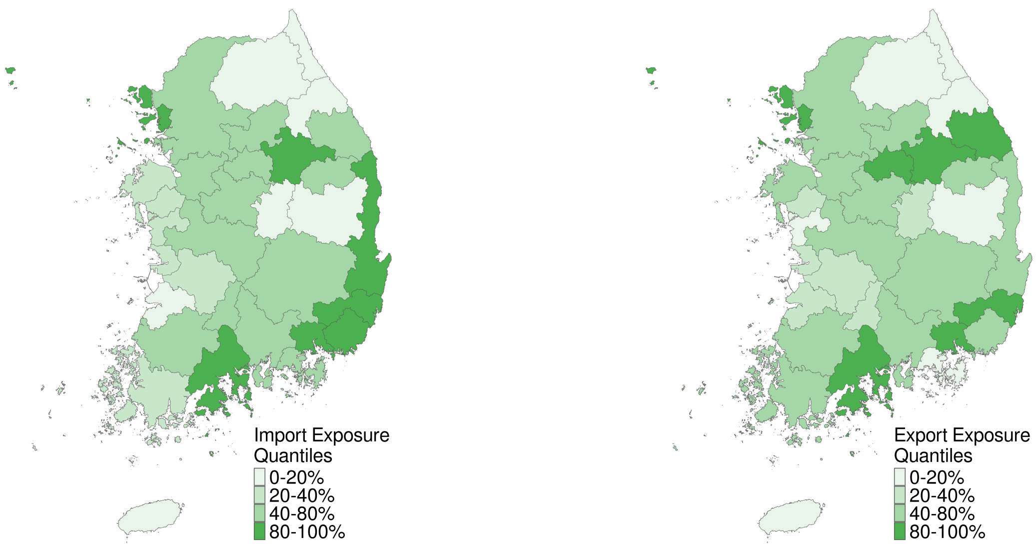
To examine the effect of trade shocks at the regional level, we need to distribute Korea's trade volumes with China across commuting zones in South Korea. We construct this local labor market exposure measure primarily à la Autor, Dorn, and Hanson (2013). However, our specification differs in ways that enrich past studies of the China trade shock. First, in addition to the import competition channel, we also consider an export expansion margin (e.g., Dauth, Findeisen, and Suedekum 2014; Choi and Xu 2020). The China trade shock can exert two opposing forces on South Korean manufacturing, particularly through the East Asian global value chain. These forces are the export-creating channel (which increases Chinese demand for Korean products) and the conventional import competition channel. Failing to account for both channels may result in a biased understanding of the effects of the China trade shock.[4] In addition to considering the export-creating channel, we decompose the trade shock by origin and destination. Past studies of the China trade shock and its impact on migration have focused primarily on the origin trade shock using net population changes in each region (Greenland, Lopresti, and McHenry 2019; Twinam 2022). Our specification extends these studies by explicitly separating the trade shock into origin and destination components. Moreover, we use internal migration flows between regions rather than net population changes within a region. This allows us to more accurately assess the impact of both origin and destination trade shocks on internal migration. In summary, we distribute Chinese imports and exports to each commuting zone based on its respective share of national industry employment. For convenience, we present below the equation only for import competition, as the export opportunity measure is constructed analogously:

$$\Delta IP_{ct} = \sum_i \frac{L_{ict}}{L_{ct}} \cdot \frac{\Delta M_{it}}{L_{it}} \tag{1}$$

where c, i, and t refer to commuting zone, industry, and time, respectively. L_{ict} is employment at the start of the period (i.e., 2001) in industry i in region c, and L_{it} refers to total employment at the start of the period (i.e., 2001) in industry i in South Korea. L_{ct} is total employment in region c at the start of the period (i.e., 2001). ΔM_{it} is the observed change in total Korean imports from China in industry i between the start and end of the period. The source for the trade data ΔM_{it} is described in Section 2.2. For employment data, we use Korea's Census on Establishments, an annual survey covering approximately 4.4 million establishments with one or more employees operating in Korea. This dataset provides information on employee counts, industry codes, and locations for all establishments within South Korea. Our data cover the years from 2001 to 2019. We segment these 19 years into two distinct periods denoted $t = 1$ and $t = 2$. Here, $t = 1$ corresponds to the period from 2001 to 2010, while $t = 2$ corresponds to the period from 2010 to 2019. With the data described above, we can compute each term in equation (1). For period $t = 1$ (and similarly for $t = 2$), ΔM_{it} refers to the change in total Korean imports from China in industry i between 2001

4. The importance of accounting for this additional dimension of exposure in countries like Korea (and the problem of not doing so) is discussed in more detail in the cited papers.

and 2010 (or between 2010 and 2019). Throughout our analysis, import and export exposure are expressed in \$1,000 USD. Additionally, the values of imports and exports in 2001 and 2010 are adjusted to 2019 dollars to account for inflation. For export exposure, all variables remain the same, with the exception of ΔM_{it}, which is adjusted to represent Korean exports to China. We denote export exposure in commuting zone c by ΔEX_{ct}. In Figure 2, we visualize the distribution of trade shocks across local labor markets for period 1 (2001–2010) by mapping import and export exposures across commuting zones in quantiles. As in the



(a) Import shock (b) Export shock

Figure 2: Map of Trade Shocks (2001–2010)

Notes: Each figure plots the import and export shock for each local labor market in South Korea. For visualization, values are given in quantiles.

existing literature on estimating the causal effect of the China trade shock, our estimation may suffer from endogeneity. To alleviate this concern, we adopt two complementary instrumental variable strategies that leverage identification "from the shifts" as discussed in Borusyak, Hull, and Jaravel (2025). Specifically, we construct shift-share instruments and argue that the share-weighted average of the shifts is as-good-as-random.

Our first strategy follows the approach of Autor, Dorn, and Hanson (2013) (hereafter ADH). We construct instruments for both import and export shocks using trade flows between China and a set of other high-income countries. Specifically, we use Australia, Denmark, Finland, Germany, New Zealand, Spain, and Switzerland as the reference countries, excluding Japan from the ADH-style instrument. The instrument takes the following form:

$$\Delta IP_{jct} = \sum_{i} \frac{L_{ict-1}}{L_{it-1}} \cdot \frac{\Delta M_{jit}}{L_{ct}}, \tag{2}$$

where the instrumental variable differs from the specification in equation (1) in two key respects. First, we use imports from China to the reference countries (ΔM_{jit}) instead of Korean imports. Second, we use lagged employment levels $\left(\frac{L_{ict-1}}{L_{it-1}}\right)$. Specifically, we use employment levels from 1999 as our lag, since concurrent employment levels may be affected by anticipated China trade.[5] The instrumental variable for export exposure is constructed analogously and is denoted by ΔEX_{jit}. Our second strategy retains the ADH-style instrument for the import shock but uses a Japan-based instrument for the export shock.[6] The motivation for this alternative is as follows. Unlike the import shock, the export shock captures the gains Korea accrues from exporting intermediate and capital goods to China as the latter becomes more deeply integrated into the global market. This feature of the export channel may be specific to Korea—and to other economies embedded in East Asian supply chains, such as Japan—rather than reflecting patterns typical of developed countries more broadly. Given this unique regional supply chain linkage, we exclude Japan from the ADH reference group and instead use Japanese exports to China as a separate instrument for the Korean export shock. This allows us to exploit the fact that Japan's export relationship with China is likely to be more informative about the supply-side forces relevant to Korea's export opportunities than the trade patterns of geographically and economically more distant high-income countries. We believe presenting results under both IV strategies—the pure ADH approach and the combined ADH–Japan approach—offers additional insight into the robustness of our findings. Our crucial assumption underlying both shift-share variables is that the shift component—constructed using export and import trade shifts from countries other than South Korea—is plausibly exogenous to unobservables that could directly affect changes in migration. To support our claim, we conduct various robustness checks in Section 4.2, following the best practices outlined in Borusyak, Hull, and Jaravel (2025). In our baseline results, columns (1) of Table 2 report estimates using the ADH instruments for all shocks, while columns (2) use the ADH instruments for import shocks and the Japan-based instrument for export shocks. One of the key challenges in constructing local exposure to trade shocks is computing ΔM_{it} and ΔM_{jit}: we need to concord trade data at the 6-digit

5. We note that our baseline shares are constructed from 1999 data, partly due to data availability constraints. While this timing closely precedes our analysis period beginning in 2001—consistent with the guidance in Borusyak, Hull, and Jaravel (2025) to lag shares to the beginning of the natural experiment—we acknowledge that earlier shares could further strengthen the exogeneity of the instrument, and readers should interpret our results with this caveat in mind.

6. This setup aligns with the identification strategy used in Choi and Xu (2020), which also analyzes the impact of the China shock in the case of South Korea using Japan as IV.

HS product level to the 5-digit Korean Standard Industrial Classification (KSIC) industry level. By constructing and following a consistent methodology, we successfully concord product-level trade shocks to the industry level. In Appendix D, we provide a more detailed description of this crosswalk from HS product codes to KSIC industry codes.

3 Empirical Specification

After constructing local exposure to trade shocks and the corresponding instrumental variables, we specify the following 2SLS regression with multiple endogenous variables:

$$\begin{aligned}\Delta \log(m_{odt}) = {} & \beta_1 x^{\text{imp}}_{o,t} + \beta_2 x^{\text{imp}}_{d,t} + \beta_3 x^{\text{exp}}_{o,t} + \beta_4 x^{\text{exp}}_{d,t} \\ & + X'_{odt}\Gamma + \alpha_o + \alpha_d + \alpha_t + \varepsilon_{odt},\end{aligned} \tag{3}$$

where $\Delta \log(m_{odt})$ denotes the change in the log of bilateral migration from origin district o to destination district d over period t.[7] Following the construction of the shock exposure, we use change from 2001 to 2010 as period 1 and 2010 to 2019 as period 2. As in our baseline, we consider only bilateral migration in which migrants move across two different commuting zones, since our local exposure to trade shocks is constructed at the commuting zone level. Note that the unit of observation for migration flows is the district pair, while the trade shock regressors are measured at the commuting zone level: each district inherits the trade exposure of the commuting zone to which it belongs. This structure allows us to exploit fine-grained variation in bilateral migration flows while relying on economically meaningful labor market definitions for the construction of trade shocks. In equation (3), we include all four trade shock variables separately: $x^{\text{imp}}_{o,t}$ and $x^{\text{imp}}_{d,t}$ denote import competition exposure in the origin and destination commuting zones, respectively, while $x^{\text{exp}}_{o,t}$ and $x^{\text{exp}}_{d,t}$ denote export expansion exposure in the origin and destination commuting zones.[8] X'_{odt} is a vector of "sum of shares" controls discussed in Borusyak, Hull, and Jaravel (2021) to address the incomplete shares issue that can arise in shift-share instrumental variable designs. α_o, α_d, and α_t are commuting zone origin, commuting zone destination, and period fixed effects, respectively.

Our coefficients of interest are β_1 through β_4 in equation (3). In equation (3), β_1 and β_3 capture how import competition and export expansion in the origin commuting zone affect bilateral out-migration, while β_2 and β_4 capture the analogous effects of trade shocks in the destination commuting zone on bilateral in-migration. In all specifications, standard errors

7. We use the change in log migration as our dependent variable rather than the level, as this formulation is likely less noisy given that substantial baseline migration between locations would have occurred even absent the trade shocks under study. We thank an anonymous referee for guidance on this specification.

8. For convenience, we refer to these four variables in our regression tables as Import (o), Import (d), Export (o), and Export (d), respectively.

are clustered at the commuting zone pair level. The baseline regressions are weighted by origin population.

4 Results

4.1 Baseline Results

We now move on to our baseline regression results. Table 2 shows the 2SLS estimates of the impact of the China trade shock on internal migration. The first column shows the regression results for equation (3) using ADH IV for import and export shock and the second column shows the results using ADH IV for import shock and Japan IV for export shock.

Table 2: Baseline 2SLS Results

	Δ log(migration)	
	(1)	(2)
Import (d)	0.007	-0.008
	(0.083)	(0.054)
Import (o)	0.255***	0.235***
	(0.085)	(0.076)
Export (d)	0.003	0.013
	(0.043)	(0.019)
Export (o)	-0.133***	-0.118***
	(0.046)	(0.041)
Observations	84,089	84,089
F-test (1st stage), Import (d)	24,493.1	44,337.2
F-test (1st stage), Import (o)	29,300.6	59,868.6
F-test (1st stage), Export (d)	4,915.3	20,847.5
F-test (1st stage), Export (o)	9,044.1	18,122.4
CZ (destination) fixed effects	✓	✓
CZ (origin) fixed effects	✓	✓
Period fixed effects	✓	✓

Notes: All regressions in the table include the same set of control variables mentioned in our empirical specification section. Column (1) uses ADH-style instruments for both import and export exposure. Column (2) uses an ADH-style instrument for import exposure and a Japan-based instrument for export exposure. For the region fixed effects, we include origin commuting zone fixed effects and destination commuting zone fixed effects. Regression estimates are weighted by the initial population in the year 2001. Standard errors are clustered at the CZ pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Before turning to the second-stage estimates, we note that the first-stage diagnostics strongly support the relevance of our instruments. Across all specifications, the first-stage F-statistics for each endogenous variable comfortably exceed conventional thresholds, alleviating concerns about weak instruments. For brevity, we summarize the first-stage results for the all-ADH specification reported in Appendix Table B.1, where each column corresponds to one of the four endogenous variables. Each instrument loads strongly and significantly onto its intended endogenous variable. Specifically, the ADH import instrument at the destination (origin) enters with a coefficient of 0.011 (0.009) in the import exposure equation for the destination (origin), and the ADH export instrument at the destination (origin) enters with a coefficient of 0.047 (0.037) in the corresponding export exposure equation. Since both the instruments and the endogenous variables are expressed in \$1,000 per worker, these coefficients indicate that a \$1,000-per-worker increase in the instrument translates into approximately \$11 and \$9 per worker increases in actual import exposure at the destination and origin, respectively, and \$47 and \$37 per worker increases in actual export exposure. Results under the ADH–Japan IV specification, reported in Appendix Table B.2, are qualitatively similar: each instrument loads strongly onto its intended endogenous variable, though the ADH import IV does not yield a statistically significant coefficient in the origin import equation when paired with the Japan IV. As we show in the second-stage results, the origin-side import effects nonetheless remain economically sensible and achieve statistical significance under the all-ADH specification, suggesting that the overall instrument set provides sufficient identifying variation for each endogenous variable.

In Table 2, the most striking result in all specifications is that the origin-side trade shocks are the primary driver of bilateral migration responses to the China shock. Import competition in the origin commuting zone has a positive and highly significant effect on bilateral migration in all columns. The estimates are 0.255 and 0.235 in columns (1) and (2), respectively, implying that a \$1,000 increase in origin import exposure per worker raises bilateral out-migration by roughly 23–25%. Export expansion in the origin commuting zone has a negative and highly significant effect on bilateral migration in all columns. The estimates are -0.133 and -0.118 in columns (1) and (2), respectively, implying that a \$1,000 increase in origin export exposure per worker hampers bilateral out-migration by roughly 12–13%. These origin-side results paint a coherent picture: import competition pushes workers out of their commuting zone, while export growth helps retain them.

Trade shocks at the destination, by comparison, play a more limited role. Import competition in the destination is negligible in magnitude and statistically insignificant across all specifications. Destination export expansion is likewise insignificant across all specifications. This provides suggestive evidence that it is primarily deteriorating conditions at the origin—rather than improving opportunities at the destination—that trigger migration in response to trade shocks.

The dominance of origin-side trade shocks carries an important implication for the existing literature. Most prior studies on trade liberalization and internal migration have focused on the impact of a region's import competition on net population changes (Autor, Dorn, and Hanson 2013; Greenland, Lopresti, and McHenry 2019; Balsvik, Jensen, and Salvanes 2015; Donoso, Martín, and Minondo 2015), and have often found only minor or insignificant effects—the so-called "missing migration" puzzle. Our bilateral framework reveals that both import competition and export expansion significantly affect out-migration from exposed regions. A key reason prior studies may have failed to detect these effects is their reliance on net population measures, which conflate origin push and destination pull forces. Because destination-side shocks tend to play a relatively muted role, net migration aggregates can obscure the underlying mobility response. By separately identifying origin and destination channels, our approach uncovers a clear push effect of import competition and a pull effect of export expansion—patterns that remain masked in analyses based solely on aggregate net population changes.

4.2 Robustness Checks

We next assess the robustness of our baseline results in light of recent recommendations in the shift–share instrument literature. Because our identification strategy hinges on the exogeneity of the shock, following the logic of Borusyak, Hull, and Jaravel (2025), we implement their suggested diagnostic procedures, with particular emphasis on regional and industry balance tests based on pre-treatment characteristics. For brevity, the full set of regression results from these robustness exercises is reported in Appendix C.

Following Borusyak, Hull, and Jaravel (2025), we conduct regional balance tests to assess whether our shift-share instruments are correlated with predetermined commuting zone characteristics. Specifically, we regress 1990-era measures of regional college share, foreign-born share, female employment share, and out-migration change over the period 1996–2000 on each of our instruments. A key challenge in implementing these tests is that fine-grained Korean regional data prior to 2001 are severely limited. We manually collected 1990-era variables from the Korean Statistical Information Service (KOSIS) website and constructed commuting zone–level measures where possible. Several variables could only be obtained imperfectly: inter-regional migration data for 1996–2000 cover only out-migration flows, and female employment rates are reported at the province ("si-do") level, which does not fully overlap with commuting zone boundaries. For such province-level variables, we do our best to match by computing each commuting zone's population share within its province and allocating rates proportionally—commuting zones falling entirely within one province receive that province's rate directly, while cross-province commuting zones receive a population-weighted average.

Despite these constraints, Appendix Table C.1 shows that coefficients from regressions of each balance variable on each instrument (ADH import, ADH export, and Japan export) are uniformly small and statistically insignificant, providing no evidence of systematic confounding. We further include these variables as controls in the main regression, interacted with period indicators (Table C.2). The inclusion of additional pre-determined controls does lead to changes in the estimates, but it is not unexpected. The constructed controls are necessarily coarse and likely introduce additional measurement error, which may absorb genuine variation alongside noise and reduce statistical power. Importantly, however, the signs of the estimates remain stable (The estimates are also statistically significant at the 10% level or better) and continue to align with the expected economic mechanisms. Greater import competition at the origin increases out-migration, while stronger export exposure at the origin decreased out-migration.

Taken together, the broadly insignificant balance coefficients reported in Table C.1 and the persistence of statistically significant effects provide reassuring evidence in favor of the identifying assumptions underlying the ADH-based strategy. Even when conditioning on these admittedly imperfect pre-determined controls, the results remain robust.

We also conduct industry-level balance tests following Borusyak, Hull, and Jaravel (2025) to assess whether our shocks are correlated with predetermined industry characteristics. As with the regional balance tests, a key constraint is that Korean industry-level data prior to 2001 are severely limited. We manually collected the best available pre-treatment variables from KOSIS: 1995 average wages and 2000 daily computer usage rates, both at the two-digit KSIC industry level. Due to data limitations, we compute weighted averages of the shift-share instruments at the two-digit level and conduct the balance test at this level of aggregation. Appendix Table C.3 shows that coefficients from regressions of each balance variable on each instrument (ADH import, ADH export, and Japan export) are small and statistically insignificant, providing no evidence of systematic confounding with respect to certain predetermined industry characteristics that were available to us. Taken together, the broadly insignificant balance coefficients in Appendix Tables C.1 and C.3 provide reasonable support for our identifying assumptions.

Another robustness check mentioned in Borusyak, Hull, and Jaravel (2025) is to correct standard errors by estimating the shift–share IV regression at the same level at which the shocks are assigned. However, implementing this approach is particularly challenging in our setting because our main specification includes multiple (four) endogenous variables. In fact, Borusyak, Hull, and Jaravel (2025) note in their Supplementary Appendix that "getting exposure-robust standard errors may be more challenging in this case," as it requires deriving an equivalent shift-level representation of the estimator in terms of moment conditions that no longer correspond to a simple IV framework. Our specification is further complicated by the use of a bilateral construction, in contrast to the unilateral exposure structures commonly employed in the shift–share literature. To the best of our knowledge, this correction has not yet been implemented in comparable empirical settings. For this reason, we do not apply the procedure in our baseline analysis. Nonetheless, we discuss it explicitly to highlight an important limitation concerning the reported standard errors in our regression tables. We leave the implementation of this correction to future research.

5 Heterogeneous Effects of the Trade Shock

We now further investigate heterogeneous impacts of the trade shock on internal migration flows by exploring across age groups and household size. By decomposing migration into various dimensions, we can gain a more comprehensive understanding of which specific groups are most affected and under what conditions. This approach may allow us to pinpoint the link between the trade shock and migration flows, thus providing a deeper understanding of mechanisms.

5.1 Heterogeneity by Age

We first investigate the presence of heterogeneous migration responses across different age cohorts. This decomposition is useful as it may help identify which segments of the workforce are most sensitive to trade-induced labor market disruptions.

To accomplish this, we estimate our baseline 2SLS specification separately for five age cohorts based on the head of household's age: 25–34, 35–44, 45–54, 55–64, and 65 or older. The results, presented in Table 3, reveal a differential pattern of age-dependent mobility.

The migration response is most pronounced and statistically significant among primary working-age individuals, especially those aged 35–54. For the 35–44 age group, the coefficient for origin import shocks is 0.214, while for the 45–54 group, it is 0.202. Similarly, origin export shocks significantly reduce out-migration for these same cohorts, with coefficients of -0.109 and -0.104, respectively. These findings suggest that workers in the middle of their careers are highly sensitive to trade-induced shifts in local economic conditions at their origin, potentially due to higher stakes in labor market outcomes compared to younger or older retired cohorts.

In contrast, the migration behavior of the youngest (25–34) and oldest (55+) cohorts appears less responsive to trade shocks. While the youngest cohort shows a marginally significant response to origin shocks, the magnitudes are smaller than those of the 35–54 groups. For those aged 55 and above, the coefficients for both import and export shocks at the origin are small and fail to reach statistical significance. This lack of response among older populations is consistent with shorter remaining work horizons[9] and potentially higher moving costs. Overall, this result also aligns with Pierce and Schott (2020) where they find that the effects of China trade shock were present primarily among working-age whites. Similar to the literature, the results seem to indicate that working-age head of households are relatively more responsive to the trade shock.

Table 3: 2SLS Results by age

	Δ log(migration)				
Age	25-34	35-44	45-54	55-64	65+
	(1)	(2)	(3)	(4)	(5)
Import (d)	0.057	-0.044	-0.037	0.018	-0.072
	(0.047)	(0.054)	(0.049)	(0.051)	(0.048)
Import (o)	0.126*	0.214**	0.202**	0.014	0.097
	(0.068)	(0.092)	(0.086)	(0.088)	(0.098)
Export (d)	-0.021	0.018	0.017	-0.003	0.030
	(0.021)	(0.020)	(0.017)	(0.019)	(0.019)
Export (o)	-0.066*	-0.109**	-0.104**	-0.010	-0.079
	(0.036)	(0.049)	(0.050)	(0.048)	(0.052)
Observations	54,067	46,267	39,604	28,747	23,763
F-test (1st stage), Import (d)	29,761.4	24,920.8	21,333.0	15,680.8	13,142.6
F-test (1st stage), Import (o)	43,241.8	39,510.8	35,807.9	29,247.0	26,184.7
F-test (1st stage), Export (d)	13,936.0	11,389.8	9,500.0	6,309.6	4,662.9
F-test (1st stage), Export (o)	12,109.1	10,735.1	9,416.9	7,395.3	6,305.0
CZ (destination) fixed effects	✓	✓	✓	✓	✓
CZ (origin) fixed effects	✓	✓	✓	✓	✓
Period fixed effects	✓	✓	✓	✓	✓

Notes: All regressions in the table include the same set of control variables mentioned in our empirical specification section. All columns use an ADH-style instrument for import exposure and a Japan-based instrument for export exposure. For the region fixed effects, we include origin commuting zone fixed effects and destination commuting zone fixed effects. Regression estimates are weighted by the initial population in the year 2001. Standard errors are clustered at the CZ pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Heterogeneity by Age and Household Structure

Our preceding heterogeneity analyses indicate that the impact of trade shocks is not uniform, with differential effects concentrated primarily among the working-age population. To better understand the mechanisms underlying these disparities, we refine our focus along two key

9. Statutory retirement age for South Korea is 60.

demographic dimensions: age cohorts and household structure—specifically, the distinction between single-person and multi-person households.

If trade-induced economic conditions indeed drive migration decisions, single-person households are more likely to exhibit greater responsiveness to local economic shocks than multi-person households. Compared with single individuals, multi-person households may face higher mobility costs due to spousal employment constraints, children's schooling considerations, and other family-related commitments. Such factors can limit their ability to relocate in response to adverse local labor market shocks.

Table 4: 2SLS results by age (single-person household)

	Δ log(migration)			
Age	25-34	35-44	45-54	55-64
	(1)	(2)	(3)	(4)
Import (d)	0.045	-0.028	-0.029	0.049
	(0.049)	(0.048)	(0.055)	(0.036)
Import (o)	0.100	0.246**	0.226**	0.092
	(0.065)	(0.103)	(0.103)	(0.071)
Export (d)	-0.020	0.014	0.012	-0.016
	(0.023)	(0.019)	(0.019)	(0.013)
Export (o)	-0.054	-0.142**	-0.125**	-0.046
	(0.034)	(0.055)	(0.059)	(0.043)
Observations	49,523	37,261	32,339	23,230
F-test (1st stage), Import (d)	27,452.9	20,560.1	17,929.6	13,070.0
F-test (1st stage), Import (o)	40,032.5	33,547.1	31,369.3	25,890.1
F-test (1st stage), Export (d)	12,723.4	8,968.5	7,717.3	5,033.8
F-test (1st stage), Export (o)	11,133.1	8,762.3	7,917.8	6,089.7
CZ (destination) fixed effects	✓	✓	✓	✓
CZ (origin) fixed effects	✓	✓	✓	✓
Period fixed effects	✓	✓	✓	✓

Notes: All regressions in the table include the same set of control variables mentioned in our empirical specification section. All columns use an ADH-style instrument for import exposure and a Japan-based instrument for export exposure. For the region fixed effects, we include origin commuting zone fixed effects and destination commuting zone fixed effects. Regression estimates are weighted by the initial population in the year 2001. Standard errors are clustered at the CZ pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To examine this mechanism, we extend our heterogeneity analysis by investigating the interaction between age and household composition. To this end, we estimate the migration responses of household heads by age cohort, while further stratifying the sample by household size. Tables 4 and Table 5 report these estimates. This exercise allows us to test whether prime-age workers in single-person households, who may face the highest exposure to risk with the fewest safety nets, exhibit distinct migration patterns compared to those in multi-person households or different age brackets. Our results indicate that single-person households (in Table 4) exhibit greater responsiveness to trade shocks relative to multi-person households (in Table 5).

Table 5: 2SLS results by age (multi-person household)

	Δ log(migration)			
Age	25-34	35-44	45-54	55-64
	(1)	(2)	(3)	(4)
Import (d)	0.064	0.031	0.020	-0.113
	(0.062)	(0.063)	(0.057)	(0.076)
Import (o)	0.181*	0.074	0.070	-0.162
	(0.093)	(0.080)	(0.074)	(0.111)
Export (d)	-0.015	-0.010	0.006	0.044
	(0.028)	(0.025)	(0.025)	(0.038)
Export (o)	-0.081	-0.034	-0.029	0.087
	(0.050)	(0.045)	(0.045)	(0.053)
Observations	21,716	26,050	17,168	9,005
F-test (1st stage), Import (d)	14,688.2	16,120.8	10,835.3	6,068.9
F-test (1st stage), Import (o)	25,392.4	27,427.7	20,024.6	12,170.8
F-test (1st stage), Export (d)	4,811.7	5,365.9	3,335.9	1,542.6
F-test (1st stage), Export (o)	5,964.2	6,761.6	4,626.4	2,931.6
CZ (destination) fixed effects	✓	✓	✓	✓
CZ (origin) fixed effects	✓	✓	✓	✓
Period fixed effects	✓	✓	✓	✓

Notes: All regressions in the table include the same set of control variables mentioned in our empirical specification section. All columns use an ADH-style instrument for import exposure and a Japan-based instrument for export exposure. For the region fixed effects, we include origin commuting zone fixed effects and destination commuting zone fixed effects. Regression estimates are weighted by the initial population in the year 2001. Standard errors are clustered at the CZ pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusion

For the past few decades, much attention has been paid to identifying the process of labor reallocation in response to trade shocks. However, various empirical studies have found only marginal or limited evidence of such reallocation. This may be partially due to limitations in the data available to precisely examine the effect of trade shocks on internal migration.

This paper addresses this largely unanswered question, the "missing migration puzzle", by providing novel data on migration. Leveraging detailed bilateral migration flows covering the entire population of Korea, this paper provides new evidence that labor reallocation in response to trade shocks occurs through out-migration rather than in-migration. In addition to introducing bilateral migration flows to separate the impact of trade shocks by destination and origin, we also decompose the China shock into two channels: (i) import competition and (ii) export expansion. By implementing this decomposition, we obtain a more precise estimate of the impact of trade shocks. Absent this refinement, estimates of the broader migration effects may be biased.

In summary, the China trade shock primarily influences out-migration rather than in-migration across regions. By isolating export and import channels, we find that export shocks decrease out-migration, while import shocks accelerate it. These effects are most pronounced among working-age household heads aged 35 to 54. Furthermore, single households exhibit higher responsiveness, suggesting that smaller household units are more sensitive to trade-induced economic shifts, consistent with lower mobility costs relative to multi-person households.

Taken together, our results indicate that trade shocks are associated with meaningful migration responses, particularly among prime-age individuals facing relatively lower mobility costs. These patterns suggest that spatial adjustment to trade shocks operates through specific demographic groups and household structures. More broadly, our findings imply that limited evidence of migration in prior studies may partly reflect the constraints of aggregate net population measures rather than the absence of mobility responses.

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A Appendix

A.1 Data on Commuting Zone Characteristics

Most of the data for capturing regional characteristics and demographics (population, employment, gender ratio, etc) are from Korean Statistical Information Service (KOSIS) by Ministry of Statistics in South Korea. For most of our analysis, we use data from the year 2001 or earlier to capture the foundational characteristics of districts (or commuting zones) within South Korea prior to the onset of the China trade shock.

Table A.1 displays overall summary statistics of our data. Each panel features our main variables we use throughout our analysis. Panel A reports share of the cumulative (2001-2020) migrants moving across commuting zones out of total migration. We also show total number and the share of moving migrants by gender and age of the head of household (in millions). Panel B reports data related to employment in commuting zone such as average logarithmic value of total number of establishments, total employments and manufacturing employments for year 1999, 2000, 2001, 2010, and 2019. Finally, Panel C reports summary statistics for our dependent variable (change in migration) and main regressors (import/export exposure).

Table A.1: Summary Statistics

Panel A: Migration Rates (Across commuting zone)					
		Cumulative, 2001-2020		**Total migrants**	
Total migrants share		0.40		101.87	
Male migrants share		0.35		53.41	
Female migrants share		0.39		21.41	
Age 25-34 migrants share		0.39		21.67	
Age 35-44 migrants share		0.34		22.55	
Age 45-54 migrants share		0.30		14.62	
Age 55-64 migrants share		0.30		7.03	
Age 65+ migrants share		0.34		4.09	
Panel B: Employment by CZ					
	1999	**2000**	**2001**	**2010**	**2019**
Average Log(Employment)	10.32	10.36	10.37	10.57	10.87
Average Log(Manufacturing employment)	8.31	8.36	8.41	8.37	8.64
Panel C: Change in migration and Import/Export exposure					
	Mean	**SD**	**25th percentile**	**75th percentile**	
Δ log(migration)	-0.1	0.73	-0.51	0.29	
Import exposure (x^{imp})	2.28	2.01	0.81	3.05	
Export exposure (x^{exp})	3.28	5.63	0.32	3.28	
N of districts	225 districts				
N of commuting zone	33 commuting zones				

Notes: All values are rounded to 2 decimal place. Values for "Total migrants" are in millions. Due to some NA values in the migration data, total number of migrants by group does not fully add up to the total number of migrants.

B First-stage Results

B.1 Only using ADH IV

	Import (d) (1)	Import (o) (2)	Export (d) (3)	Export (o) (4)
IV for Import (d)	0.011***	0.0007	3.03×10^{-5}	0.0004
	(0.002)	(0.002)	(0.009)	(0.003)
IV for Import (o)	0.0009	0.009***	0.0008	-0.001
	(0.002)	(0.002)	(0.006)	(0.004)
IV for Export (d)	0.018***	-0.0004	0.047***	0.0001
	(0.002)	(0.001)	(0.010)	(0.002)
IV for Export (o)	-0.0003	0.017***	0.0002	0.037***
	(0.001)	(0.0008)	(0.004)	(0.003)
Observations	84,089	84,089	84,089	84,089
F-test (1st stage)	24,493.1	29,300.6	4,915.3	9,044.1
CZ (destination) fixed effects	✓	✓	✓	✓
CZ (origin) fixed effects	✓	✓	✓	✓
Period fixed effects	✓	✓	✓	✓

Notes. All regressions in the table include the same set of control variables mentioned in our empirical specification section. All columns use an ADH-style instrument for import and export exposure. For the region fixed effects, we include origin commuting zone fixed effects and destination commuting zone fixed effects. Regression estimates are weighted by the initial population in the year 2001. Standard errors are clustered at the CZ pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Using ADH IV for Import Shock and Japan IV for Export Shock

	Import (d) (1)	Import (o) (2)	Export (d) (3)	Export (o) (4)
IV for Import (d)	0.008***	0.0004	-0.022***	-0.0003
	(0.002)	(0.001)	(0.007)	(0.003)
IV for Import (o)	0.001	0.002	-0.0004	-0.019***
	(0.002)	(0.002)	(0.006)	(0.005)
IV for Export (d)	0.127***	-0.002	0.477***	0.001
	(0.010)	(0.004)	(0.048)	(0.010)
IV for Export (o)	-0.004	0.159***	0.005	0.374***
	(0.007)	(0.007)	(0.025)	(0.029)
Observations	84,089	84,089	84,089	84,089
F-test (1st stage)	44,337.2	59,868.6	20,847.5	18,122.4
CZ (destination) fixed effects	✓	✓	✓	✓
CZ (origin) fixed effects	✓	✓	✓	✓
Period fixed effects	✓	✓	✓	✓

Notes. All regressions in the table include the same set of control variables mentioned in our empirical specification section. All columns use an ADH-style instrument for import exposure and a Japan-based instrument for export exposure. For the region fixed effects, we include origin commuting zone fixed effects and destination commuting zone fixed effects. Regression estimates are weighted by the initial population in the year 2001. Standard errors are clustered at the CZ pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Robustness Checks

C.1 Regional Balance Test

Panel A

	College share			Foreign-born share		
	(1)	(2)	(3)	(4)	(5)	(6)
Import IV	0.036			0.0007		
	(0.086)			(0.0008)		
Export IV		-0.022	0.046		-0.0001	0.001
		(0.046)	(0.387)		(0.0005)	(0.004)
IV	ADH (import)	ADH (export)	JPN (export)	ADH (import)	ADH (export)	JPN (export)
Observations	66	66	66	66	66	66

Panel B

	Female employment share			Migration change (2000 - 1996)		
	(1)	(2)	(3)	(4)	(5)	(6)
Import IV	-0.118			-0.125		
	(0.178)			(0.698)		
Export IV		0.066	-0.240		-0.271	-2.71
		(0.097)	(0.806)		(0.375)	(2.12)
IV	ADH (import)	ADH (export)	JPN (export)	ADH (import)	ADH (export)	JPN (export)
Observations	66	66	66	221	221	221

Notes. This table reports coefficients from regressions of commuting zone–level covariates and a pre-trend variable (migration change) on each shift-share instrument, controlling for period indicators interacted with the lagged manufacturing share to account for incomplete shares. Row "IV" indicates which instrument variable was used for implementing the balance test. All specifications are estimated at the commuting zone level, except for migration change, which is estimated at the district level—the unit of analysis in our main regressions—excluding districts for which data are unavailable. Independent variables (exposure shock IV) were divided by 1,000 for better interpretation of the coefficients; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Adding Pre-treatment Controls

	Δ log(migration) (1)	(2)
Import (d)	0.062	0.026
	(0.044)	(0.035)
Import (o)	0.085*	0.094**
	(0.048)	(0.041)
Export (d)	-0.023	0.002
	(0.026)	(0.013)
Export (o)	-0.046*	-0.046**
	(0.025)	(0.021)
Observations	84,089	84,089
F-test (1st stage), Import (d)	17,942.3	41,886.3
F-test (1st stage), Import (o)	25,659.3	59,771.3
F-test (1st stage), Export (d)	3,212.2	20,715.6
F-test (1st stage), Export (o)	8,662.5	18,349.7
CZ (destination) fixed effects	✓	✓
CZ (origin) fixed effects	✓	✓
Period fixed effects	✓	✓

Notes. In addition to the controls from the main regression specification, this table includes pre-treatment control variables interacted with period indicators. Column (1) uses an ADH-style instrument for import and export exposure. Column (2) uses an ADH-style instrument for import and Japan-based instrument for export exposure. Region fixed effects comprise both origin and destination commuting zone fixed effects. All regressions are weighted by initial population in 2001, and standard errors are clustered at the commuting zone pair level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Industry Balance Test

	Log wage (1995)			Computer share (2000)		
	(1)	(2)	(3)	(4)	(5)	(6)
Import IV	-0.0001			-0.0002		
	(0.0008)			(0.0008)		
Export IV		-0.0001	-0.002		0.0003	0.003
		(0.0008)	(0.007)		(0.0008)	(0.007)
IV	ADH (import)	ADH (export)	JPN (export)	ADH (import)	ADH (export)	JPN (export)
Observations	62	62	62	72	72	72

Notes. This table reports coefficients from regressions of industry-level (KSIC 2-digit) covariates on each shift-share instrument, controlling for period indicators. Row "IV" indicates which instrument variable was used for implementing the balance test. The number of observations varies across specifications due to differences in data availability. Independent variables (exposure shock IV) were divided by 1,000 for better interpretation of the coefficients; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Methodology for Crosswalking HS Product Codes to KSIC Industry Codes

The process of crosswalking HS product codes to KSIC industry codes is critical for ensuring consistent and comparable data across international trade statistics and domestic establishment surveys. The methodology consists of two parallel concordance tracks—one for trade data and one for employment data—both converging on the KSIC 10th revision as the common classification. The detailed procedure is as follows:

1. **Data Sources**: The trade data are drawn from the UN Comtrade database for ten developed economies: Australia, Switzerland, Germany, Denmark, Spain, Finland, the United Kingdom, Japan, South Korea, and New Zealand. All trade flows are measured bilaterally with China as the trading partner. These datasets span three reference years—2001, 2010, and 2019—each corresponding to a distinct HS revision. The non-Korean countries serve as a source of variation for constructing instrumental variables in the China shock framework.

2. **Variations in HS Codes**: The HS (Harmonized System) codes differ across the three reference years:

   - The 2001 data use the HS 1996 revision (HS1)
   - The 2010 data use the HS 2007 revision (HS3)
   - The 2019 data use the HS 2017 revision (HS5)

   All trade data are recorded at the 6-digit HS level and filtered to bilateral flows with China (partner code 156).

3. **Trade Data Concordance: HS to ISIC Rev.4**: The first stage converts HS product codes into ISIC Rev.4 (International Standard Industrial Classification, Revision 4) industry codes using the `concordance` R package (Liao et al. 2020). For each 6-digit HS code, the package returns one or more matching ISIC Rev.4 codes along with proportional weights derived from official crosswalk tables. Trade values—FOB (Free on Board) for exports and CIF (Cost, Insurance, and Freight) for imports—are multiplied by these weights and then aggregated at the ISIC Rev.4 level by country pair, year, and flow direction.

4. **Trade Data Concordance: ISIC Rev.4 to KSIC 10**: The second stage maps ISIC Rev.4 codes to KSIC 10th revision codes using an official concordance table published by Statistics Korea. Where a single ISIC Rev.4 code maps to multiple KSIC 10 codes,

trade values are distributed equally across destination codes using a weight of $1/n$, where n is the number of matched KSIC codes. The weighted values are then summed by country pair, year, flow direction, and KSIC 10 industry to produce the final trade dataset.

5. **Establishment Data and KSIC Version Harmonization**: The National Business Survey data contain establishment-level employment counts classified under three successive KSIC revisions:

   - Years 1994, 1996, 1999, 2000, and 2001 are coded under the KSIC 8th revision
   - Year 2010 is coded under the KSIC 9th revision
   - Year 2019 is coded under the KSIC 10th revision

   To harmonize all years to a common classification, we apply a two-step concordance chain. First, KSIC 8 codes are converted to KSIC 9 codes using an official crosswalk table. Second, KSIC 9 codes (including those converted from KSIC 8 as well as the 2010 data originally in KSIC 9) are converted to KSIC 10 codes. Data for 2019, already classified under KSIC 10, require no conversion.

6. **Handling Many-to-One Relationships**: In instances where multiple source codes map to a single destination code (e.g., several HS codes mapping to one ISIC code, or several KSIC 8 codes mapping to one KSIC 9 code), the aggregation is straightforward: values from the multiple source codes are summed to produce the destination code total.

7. **Handling One-to-Many Relationships**: When a single source code maps to multiple destination codes, the associated value is distributed proportionally. For the HS-to-ISIC step, the `concordance` package provides empirically derived weights reflecting the relative importance of each match. For all subsequent steps—ISIC to KSIC 10, KSIC 8 to KSIC 9, and KSIC 9 to KSIC 10—equal weights of $1/n$ are applied, where n is the number of destination codes. For example, if an ISIC code with a trade value of \$100 maps to two KSIC 10 codes, each receives \$50. The same equal-distribution logic applies to employment counts in the establishment data, which may result in non-integer employment figures.

By following this methodology, we ensure that both trade and employment data are expressed in a common KSIC 10th revision classification at the 5-digit level, providing a consistent framework for analyzing the impact of trade exposure on local labor markets.

E Methodology for Concordance of Districts

The comprehensive methodology applied for ensuring a consistent concordance of districts in the data spanning from 1996 to 2020 is delineated below:

1. **Base Units for Concordance**: The foundational unit for concordance in this data set comprises 225 districts. These districts were used as the key reference points for integrating data over the period from 1996 to 2020.

2. **District Mergers**: During the observed time frame, certain districts underwent administrative mergers. In these instances, data from previously separate districts was consolidated. For analytical consistency, we retroactively combined data from such merging districts, treating them as a single unit, even for periods prior to the official merger. This ensured uniformity across the entire time span.

3. **District Splits**: Conversely, there were occasions when a single administrative district was bifurcated into multiple distinct entities. In such scenarios, data from these newly-formed districts was aggregated back into the original singular unit for the entirety of the observational period. This approach was adopted to preserve a consistent analytical framework that allows for clear and unambiguous comparative analyses across the years.

Incorporating these strategies has been instrumental in maintaining the integrity and clarity of the regional data, thus providing a robust foundation for meaningful analysis.