Moving Under Uncertainty: Heterogeneous Migration Responses to Trade Liberalization

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Abstract

Exploiting China's accession to the WTO as a large trade shock, we show that migration and sectoral reallocation in response to trade liberalization were primarily driven by workers entering the labor market at the time of accession. To explain this heterogeneity, we develop and structurally estimate a migration model with constant relative risk aversion (CRRA) preferences, in which migration decisions depend on both expected income gains and income-risk differentials across locations and sectors. Estimated age-specific parameters reveal that risk aversion rises substantially with age. Compared with a counterfactual in which all workers are risk-neutral, our estimates indicate that the age gradient in risk aversion accounts for much of the rise in migration costs over the life cycle, particularly for inter-provincial migration.

Keywords: Internal migration, Trade liberalization, Uncertainty, Structural change, Age gradient
JEL Codes: F16, J61, O15

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1 Introduction

A burgeoning literature highlights the role of labor market adjustment in shaping both the aggregate welfare and distributional consequences of trade shocks. For example, Artuç et al. (2010) showed that sizable intersectoral switching costs slow the labor market response to trade liberalization, hindering the long-run wage equalization predicted by traditional trade models. Since then, a broader literature seeks to understand, model, and quantify mobility frictions not only across sectors but also across geographic locations in a variety of contexts (Tombe and Zhu, 2019; Fajgelbaum et al., 2018; Bryan and Morten, 2019; Morten and Oliveira, 2024; Redding, 2016; Allen and Arkolakis, 2014). Yet much of this literature treats workers as homogeneous and estimates average migration elasticities that mask important heterogeneity in adjustment behavior and, in turn, might provide an incomplete picture of the unequal distribution of gains and losses from trade shocks.

This gap is puzzling in light of the evidence on internal migration in both developed and developing countries. In a very recent review, Jia et al. (2023) show that although internal migration in the United States has declined over the past three decades, mobility remains common between labor-market entry and the mid-thirties. Similar patterns are also observed in developing countries, where younger and more educated individuals are disproportionately likely to relocate in response to expanding economic opportunities, including those generated by trade liberalization [1]. Together, these patterns point to a pronounced age gradient in geographic mobility.

Despite this evidence, it is challenging to explore the mechanisms underlying age differences in migration responses. Existing studies typically treat age as a reduced-form determinant of migration, without explicitly modeling how workers of different ages evaluate future opportunities. This limitation is particularly important in the context of trade shocks, which changes agents' expectations about the future dynamically. An influential framework developed by Kennan and Walker (2011) models migration as a forward-looking search process in which workers choose among destinations based on expected earnings. This paper builds on this insight by recognizing that future earnings are uncertain and that workers with different ages may differ in their willingness to bear such uncertainty. In particular, we provide a framework for understanding why migration responses to economic opportunities vary systematically across age groups, incorporating income uncertainty and risk preferences into migration choice.

Empirically, we use China's accession to the World Trade Organization (WTO) in 2001 as a plausibly exogenous trade shock. This setting is particularly well suited to

[1] See, for example, Dix-Carneiro (2014) for Brazil, Ghose (2026) for India, and McCaig et al. (2022); McCaig and Pavcnik (2018) for Vietnam.

our analysis because China's accession to WTO has triggered rapid and far-reaching economic transformations, generating substantial labor-market adjustments across regions and sectors. Moreover, the timing of the shock is useful for studying life-cycle differences in migration responses. We focus on cohorts defined relative to the legal working age at the time of WTO accession. Individuals born between 1986 and 1990 were between ages 11 and 15 in 2001 and entered the labor market shortly after the trade shock, whereas those born in 1984 or earlier had already passed the critical school-to-work transition when the shock occurred.

Two striking empirical regularities characterize these adjustment processes. First, as shown in Figure 1, migration rates increase gradually across birth cohorts but exhibit a pronounced discontinuity around the mid-1980s. Among individuals born in 1986—who turned 15 or 16 around the time of WTO accession—approximately 45 percent had become migrant workers by 2005, compared with only 27 percent of the 1984 birth cohort. Second, Figure 2 reveals a similar discontinuity in manufacturing employment. More than 35 percent of the 1986 cohort were employed in secondary industries (predominantly manufacturing), compared with about 25 percent of the 1984 cohort, suggesting that the expansion of trade-exposed industries disproportionately absorbed younger workers entering the labor market.

To formalize these patterns, we implement a generalized version of the empirical strategy developed by Bargain and Jonassen (2024), combining cohort-level discontinuities with prefecture-level variation in trade exposure. Using individual-level data from the 2000, 2005, 2010, and 2015 population censuses, comprising millions of observations, we compare individuals born in 1986 or later (the treatment group) with those born before 1986 (the control group) across prefectures with different exposure to trade liberalization. We find large and statistically significant effects of trade exposure on both migration and manufacturing employment among younger cohorts, while responses among older cohorts are substantially smaller or insignificant. These results indicate that the labor reallocation induced by China's WTO accession was driven overwhelmingly by workers who entered the labor market after the trade shock.

To explain the observed age-cohort differences in migration responses to the trade shock, we develop a model of migration frictions that incorporates income uncertainty and risk preferences. In the model, workers face uncertainty about earnings at potential destinations and make migration decisions under constant relative risk aversion (CRRA) preferences [2]. In this environment, workers' migration is influenced not only by expected income at the destinations relative to origin, but

[2]A recent paper by Porcher et al. (2024) examines the role of information friction (about destination wages) in migration decisions and shows that access to internet services reduces the information barrier.

also by the variance of income (income risks) at the potential destinations relative to origin. Our model gives migration flow equation between location pairs as a function of differences in their expected income, differences in their variance of income, differences in amenities, and moving costs. Two parameters govern migration costs in our model: elasticity of migration to difference in expected incomes between destination and origin location (which is standard in the literature and we assume is constant across cohorts) and elasticity of migration to difference in variances of income between destination and origin location (i.e., risk parameter), which we allow to vary across cohorts. This latter parameter is a novel feature of our model.

While the risk parameter exogenously varies across ages in our main (static) model, we present a dynamic choice problem with a life-span effect where age gradient in risk parameter appears endogenously. In this dynamic model, younger workers with longer remaining lifespan would have higher option value of migrating to high-risk, high-return locations as they have longer time to reap the benefit of a good draw. The younger workers are also better situated to absorb economic shocks as they have more time to smooth-out bad draws. Both these mechanisms generate risk parameter that endogenously varies with age. We show that this dynamic model gives migration equation that is closely related to the one from our static model. Hence, we consider our estimated migration equation as an approximation of the migration rule from the dynamic choice problem.

Migration flow equations derived from models where agents face no income uncertainty (or are risk-neutral) omit differences in variance of income between destination and origin location. If agents face income uncertainty and are not risk-neutral, this causes serious omitted variable bias in estimation of migration elasticity because the variance of income is a function of the mean. Importantly, this bias cannot be resolved by using IV estimation because any relevant instrument for the mean of income is correlated to the variance of income and thus fails the exclusion restriction. Our approach resolves this problem as it gives estimation equation of migration flow that includes differences in both mean and variance of income between destination and origin. Another identification issue is that unobserved factors, such as amenities or quality of institutions, could be correlated with mean and variances of income at destination and origin locations and influence migration flows. To address this endogeneity issue, we follow the literature and use income of neighboring provinces to construct IVs.

We use the 2005 mini-census data which includes information on birth-place, wages and sectors of employment for workers. This allows us to construct the mean and variances of wages for each province-sector-cohort cells. We aggregate the sectors into two – agriculture and non-agriculture – and construct bilateral migration flow between every province-sector pair for each cohort.

We estimate elasticity of migration flow to the difference in average destination and origin income of 3.5. Our estimates for the elasticity of migration to the difference in income variance between destination and origin ranges from 0.3 for the youngest cohorts (aged 15-19) to -1.47 for the oldest cohorts (aged 60-64), thus decreasing with cohort ages. We infer each cohort's risk preference parameter from the above two elasticities. We find risk parameters ranging from 0.14 for the youngest cohorts to 2.4 for the oldest cohorts. Our estimates consistently suggest that the youngest cohorts (aged 15-19) are far less risk-averse than their older cohorts. The degree of risk-aversion generally increases with age of cohorts, sharply rising after 50s.

Using our parameters, we infer bilateral migration costs between province-sector pairs for each cohort. We find significant migration costs averaging more than 5 times expected current utility of workers.[3] We find that the migration costs are predominantly driven by costs of moving across provinces, which are about 10 times the costs of switching sectors within a province. Most importantly, these migration costs significantly increase with cohort ages. On average, migration costs for the youngest cohorts are one-tenth of the migration costs facing the oldest cohorts. This monotonic variation in migration costs is primarily driven by their attitude towards income risks. To show this, we calculate counterfactual migration costs if all cohorts had similar risk parameter and find that the resulting migration costs are flat across cohorts.

Our findings further reveal a significant asymmetry in migration costs, particularly regarding sectoral transitions. Specifically, the cost of migrating from agriculture to non-agricultural sectors is significantly larger than that of the reverse flow—a pattern that persists for both intra- and inter-provincial movements. Moreover, migration costs between provinces are about ten times the costs of switching sectors within a province. To address the varying degrees of substitutability between jobs across sectors versus those across provinces, we extend our baseline framework to a nested migration model. The extended model provides a structure to distinguishing between inter-provincial and inter-sectoral migration elasticities. We find that the latter is more than twice the magnitude of the former. This discrepancy underscores that these two migration pathways are subject to fundamentally different cost structures.

This paper is closely related to a growing literature examining how globalization shapes internal migration. A central finding of this body of literature is that workers often respond only imperfectly to geographic and sectoral opportunities, limiting the gains from trade liberalization and exacerbating the welfare consequences of adverse import competition. For example, Facchini et al. (2019) and Zi (2025)

[3]However, compared to previous related studies, our migration cost estimates are modest. This is perhaps because these past studies generally underestimate the migration elasticity which would cause overestimation of migration costs.

show that China's WTO accession induced substantial internal migration toward regions benefiting most from export expansion, with the response concentrated among migrants lacking local Hukou status. Similarly, Dix-Carneiro and Kovak (2017) find that the regional wage disparities generated by Brazil's 1991 trade liberalization persisted for more than two decades, highlighting the slow pace of labor reallocation across regions. Focusing on the U.S., Autor et al. (2016) argues that declining geographic mobility amplified the adverse consequences of import competition in manufacturing-intensive regions. While this vibrant literature extensively investigates the spatial outcomes of trade shocks, our paper shifts the focus to the determinants of migration, which have receives less attention in recent years. In particular, we examine how income uncertainty and risk preferences shape workers' willingness to relocate, helping explain why labor reallocation remains incomplete even when substantial gains from migration exist.

This paper advances the literature on the relationship between trade liberalization and the sectoral reallocation of labor (Erten and Leight, 2021; McCaig and Pavcnik, 2018)[4]. Prominent studies have documented substantial shifts from agriculture to manufacturing following improved export access. For example, Erten and Leight (2021) demonstrate that China's expanded access to the U.S. market after 2001 accelerated the movement of workers out of agriculture and into manufacturing at the local level. The prevailing interpretation of such patterns attributes structural transformation primarily to incumbent workers switching sectors. Indeed, influential discussions of productivity-enhancing structural change often emphasize the relative ease of occupational transitions in manufacturing-led paths, as articulated by McMillan et al. (2017): "It is comparatively easy *to turn a rice farmer into a garment factory worker* ..." without requiring substantial human or physical capital investments. Yet this paper challenges that conventional view by providing robust evidence that, in the Chinese context, sectoral reallocation following WTO accession was overwhelmingly driven by the entry decisions of younger cohorts rather than by sector switching among established workers. We document discontinuous jumps in manufacturing employment shares—and corresponding sharp declines in agricultural employment—precisely for cohorts born in 1986 and in the immediately following years. These cohort-specific shifts are markedly more pronounced in prefectures with greater exposure to trade liberalization than in less-exposed areas. Consequently, the bulk of observed structural change reflects the disproportionate absorption of new labor-market entrants into the expanding manufacturing sector, rather than widespread reallocation among older cohorts. We argue that this pattern arises from systematically higher sectoral switching costs faced by older workers, whose accumulated location-, firm-, or occupation-specific human capital renders transitions

[4]See also McCaig (2011); Kis-Katos and Sparrow (2015).

substantially more costly than for youth at the outset of their careers.

This paper also contributes to the literature on the role of risk preferences in shaping economic decisions. A limited body of research, particularly in behavioral and labor economics, suggests that individual risk attitudes influence migration choices and that risk tolerance varies systematically over the life cycle, with younger individuals generally exhibiting a greater willingness to take risks than older individuals (See, for instance, Bauernschuster et al. (2014); Dohmen et al. (2011); Jaeger et al. (2010)). However, identifying the effect of risk preferences on migration decisions remains challenging because risk attitudes are inherently unobservable and may be correlated with other determinants of mobility, leading to self-selection concerns in reduced-form analysis. This paper overcomes this limitation by developing a dynamic structural model of migration that incorporates income uncertainty and heterogeneous risk preferences across age groups. The model enables us to quantify the extent to which differences in risk attitudes contribute to age-specific migration behavior and labor-market adjustment. Exploiting China's accession to the WTO as a large and plausibly exogenous trade shock, we conduct counterfactual exercises to estimate how migration elasticities and mobility costs vary across workers with different degrees of risk aversion, providing a novel explanation for incomplete labor reallocation following large economic shocks.

Our paper complements the literature on heterogeneous migration responses to trade shocks by emphasizing age as a fundamental source of heterogeneity in workers' mobility decisions. While previous studies have primarily emphasized heterogeneity across industries (Artuç et al., 2010; Attanasio et al., 2004), occupations(Artuç and McLaren, 2015), and regions of residence (Kovak, 2013), we argue that age is particularly important because migration is an intertemporal investment decision under uncertainty [5]. Younger workers have more time to recoup relocation costs and are generally more willing to bear risk, implying that the same trade shock can generate markedly different migration responses across the life cycle. By highlighting the role of age-dependent risk preferences and migration incentives, our paper provides a new perspective on the uneven adjustment of workers to trade shocks and, more broadly, to major economic disruptions such as recessions, technological change, and climate change [6].

[5] In an unpublished paper, Artuç (2012) also documents substantial age heterogeneity in workers' responses to trade shocks, showing that mobility costs increase with age and that the effects of trade liberalization vary over the life cycle. Consistent with the importance of age heterogeneity, Greenland et al. (2019) show evidence from the United States that local labor markets more exposed to import competition after China's entry into WTO slower population growth, with migration responses concentrated among younger workers and those with lower levels of education. However, neither of these two explores the underlying mechanisms that generate these age-specific adjustment patterns.

[6] For example, recent research finds that workers' responses to the Great Recession differed substantially across age groups, implying that aggregate economic shocks can generate highly

The rest of the paper is organized as follows. Section 2 describes the data and presents empirical facts. Section 3 presents our novel model of migration friction and estimation of the structural parameters and migration costs. In section 4, we present an extension of our baseline model to a nested migration model where switching sectors within a province and migration across provinces are governed by different elaticities. Section 5 discusses the estimated migration costs in comparison with self-reported migration costs from survey data. In Section 6, we present a dynamic choice model with life-span effect in which variation in risk-aversion across age appears endogenously, and demonstrate how the migration equation in our main model can be considered as an approximation to the dynamic choice model. Section 7 concludes the paper.

2 Empirical Analysis

2.1 Data

Our main dataset comes from rounds of Chinese national census data. For our analysis of trends on migration flow and sectoral allocation across cohorts, we combine successive rounds of Chinese national census data. More specifically, we use the 2000 and 2010 rounds of national census and the 2005 and 2015 mini-censuses. We use these data sets to construct prefecture-level share of workers employed in the primary, secondary, tertiary and manufacturing sectors for each of the cohorts born since 1935. We also use the data to construct the share of workers of each cohort who are migrant in the last five years before the census date. Our measure of migrants includes those who move within prefecture and between prefectures. Past studies usually focus on between prefecture migrations which underestimate the true extent of migration because they exclude some common migration patterns such as rural-urban migrations within a prefecture. We combine these data with a measure of exposure to China's accession to the U.S market at prefecture-level. We obtain data on this measure and a host of prefecture-level control variables from Facchini et al. (2019).

For our structural estimation of migration flow equation, we rely on the 2005 mini-census which includes information on employment, income, migration history and other basic characteristics of workers. We construct migration flows between provinces and sectoral changes within province for each cohorts (age groups). We choose province, instead of lower level of administrative units such as prefecture, because the sample size of the 2005 census does not allow us to construct reliable measure of bilateral migration at cohort and sector level.

unequal welfare consequences over the life cycle (Rinz, 2022; Salvanes et al., 2022).

We complement our census-based analysis with the 2007 China Household Income Project (CHIP) survey dataset. This survey includes migrants' self-reported migration costs, which we use to compare and validate our model-based estimates of migration costs at a cohort level.

We present important summary statistics on trends in manufacturing employment and migration for youth and adult workers across census rounds in Table 1. The table shows that only 8% of adult (26 or older) workers in 2000 census are migrants, compared to 24% of young (age 16-25) workers who are migrants in the same year. The share of migrant adult workers increased to 24% while the share of youth workers who are migrants increased to 52% in 2010.

The table shows similar trend in manufacturing employment rates of adults and youth. In 2000 census, 12% of adult workers and 20% of youth worked in manufacturing. These numbers increased to 17% and 31% for the adults and youth, respectively, in 2010 census. Overall, the table shows that not only are the youth becoming increasingly more mobile compared to the adults but also that they are increasingly absorbed into the manufacturing sector. Below we explore how these trends are driven by trade policy by exploiting geographic variation in exposure to trade policy change.

2.2 Methodology

To explore heterogeneous sectoral reallocation and migration responses to trade policy across cohorts, we utilize an identification strategy that combines regression discontinuity design (RDD) and generalized DID design.

The RDD component comes from discontinuous exposure to trade liberalization across cohorts. We combine such discontinuous variation with exogenous spatial variation in exposure to trade liberalization across prefectures. This spatial variation is attributed to differences in the basket of goods exported by prefectures and variation in change in tariff uncertainty across different baskets of goods (see below).

Our strategy can be viewed as a generalized version of Bargain and Jonassen (2024), who use age discontinuity in eligibility to social assistance to study its effect on employment and benefit take up.[7] Our framework is generalized because in addition to age discontinuity in exposure to trade policy change, individuals in different prefectures are exposed to trade shock to a different degree depending on the industrial composition of their prefectures and variation in the pre-liberalization tariff uncertainty across industries. Intuitively, our identification strategy can be understood as comparing the discontinuous changes shown in Figures 1 & 2 across prefectures with various degree of exposure to trade policy. In the prefectures

[7] See also Lemieux and Milligan (2008).

less exposed to the policy change, the discontinuous jumps in these figures are muted; in highly exposed prefectures the jump is significantly pronounced. We use these variations to estimate how much of the discontinuous jumps in migration and manufacturing employment rates were driven by trade liberalization.

Our main estimation equation is written as follows:

$$y_{pc} = \beta_0 + \beta_1 \Big(D_c \times \text{NTRgap}_p\Big) + \beta_2 \Big(D_c \times I_c \times \text{NTRgap}_p\Big) + \gamma_p + \gamma_c + \varepsilon_{pc} \qquad (1)$$

where y_{pc} denotes outcome variables (mainly, share of employment in manufacturing and migrant share of employment), p indexes prefectures, and c is cohorts (birth year). D_c is a dummy variable which equals 1 for cohorts born in 1986 or later and zero otherwise. Cohorts born in 1986 turn 16 years of age (legal age of employment) in 2001 when China became a member of WTO. I_c is birth year of cohorts *minus* 1986. This variable is a re-centered birth year around 1986 and in interaction with D_c captures discontinuous exposure to trade liberalization for cohorts born in 1986, relative to other cohorts.

NTRgap_p is a measure of exposure to trade liberalization across prefectures. Prior to 2001, the U.S congress votes annually to renew China's Normal Trade Relation (NTR) status in the U.S market. If China's NTR status is approved in congress, Chinese goods will be subject to low NTR tariffs (MFN tariff rates reserved for WTO members). If congress votes against China's NTR status, however, Chinese exports to the U.S. market would be subjected to very high non-NTR tariff rates (also known as column 2 tariff rates) usually imposed on nonmarket economies. The non-NTR tariff rates were determined under Smoot-Hawley Tariff Act of 1930 (Pierce and Schott, 2016). In October 2000, the U.S. congress voted to grant Permanent Normal Trade Relation (PNTR) status to China which would become effective upon China's accession to WTO in 2001. This reduced significant uncertainty faced by Chinese firms in their access to the U.S market. Moreover, because the NTR-gap, difference between the non-NTR and NTR tariff rates, varied massively across industries, the decrease in uncertainty varied across industries. We exploit this significant heterogeneity in the level of change in tariff uncertainty across industries together with geographic variation in the concentration of industries across China to construct prefecture-level exposure to trade liberalization. The resulting measure is given as $\text{NTRgap}_p = \sum_i \alpha_{pi,1999} \times \text{NTRgap}_i$, where $\alpha_{ip,1999}$ is share of prefecture p's export of good i and $\text{NTRgap}_i = \text{NonNTR tarrif}_i - \text{NTR tariff}_i$ is the difference between non-NTR tariff rate and NTR tariff rate for product i. Erten and Leight (2021) use similar methodology to study the effect of trade liberalization on structural transformation in China while Facchini et al. (2019) use it to study migration.

Alternatively, we estimate our regression using variation across census rounds for each cohort and prefecture to obtain cohort-by-prefecture-by-census round variation. We can then run the following regression.

$$\begin{aligned} y_{pct} = \beta_0 + \beta_1\Big(D_c \times \text{NTRgap}_p\Big) + \beta_2\Big(D_c \times I_c \times \text{NTRgap}_p\Big) \\ + \gamma_p + \gamma_c + \gamma_t + \varepsilon_{pct} \end{aligned} \tag{2}$$

The main difference between regression Equations (1) and (2) is that in the former, we are implicitly assuming that cohorts born in the same year have equal share of employment in a given sector (say secondary sector) across census years, up to a constant factor. If significant fraction of these cohorts change employment sector over census years, this assumption is wrong. Equation (2) does not impose this assumption but any difference in average employment share of a cohort in a given sector is subsumed in census-year fixed effects.

2.2.1 Results

Sectoral reallocation of workers: We now present our estimation results for sectoral reallocation in Table 2. The outcome variables are shares of employment in manufacturing, secondary, primary and tertiary sectors. All regressions include prefecture and cohort fixed effects and the post-1986 cohort dummy (D) interacted with the following control variables obtained from Facchini et al. (2019): export license share, foreign tariff, import tariff, production subsidy, and NTRrate.

Column (1) shows that manufacturing share of employment increased by 17.3 percentage points for cohorts born in 1986 or later relative to older cohorts in a prefecture with 100 percentage point decrease NTRgap. Column (2) shows that share of employment in the secondary sector increased by 12.3 percentage points while Column (3) shows that the share of employment in the primary sector decreased by 13.4 for cohorts born in 1986 or later relative to older cohorts. Column (4) shows that the employment share in tertiary sector did not change significantly for cohorts born in 1986 or later following trade liberalization.

To benchmark the magnitude of these estimated effects, we compare a prefecture at the 10th percentile against a prefecture at the 90th percentile. The latter experienced a decrease in NTRgap by 46.5 percentage points more than the former. Thus multiplying the estimated coefficients in Table 2 by 0.465 gives us change in employment shares for cohorts born in 1986 or later (relative to older cohorts) in a prefecture at 90th percentile of exposure to trade liberalization (relative to a prefecture at the 10th percentile). The resulting numbers are 8ppt increase in manufacturing share of employment, 5.7ppt increase in share of employment in the secondary sector, and 6.2ppt decrease in share of employment in the primary sector.

In Equation (1) and Table 2, our estimation is based on data from multiple censuses aggregated at prefecture-cohort level. An alternative to this approach is to use variations at prefecture-cohort-census round level as written in Equation (2). The results from this alternative approach are reported in Table 3. The estimated effects closely resemble their counterparts in Table 2, implying that the share of a cohort employment in a given sector remains relatively stable across census years. That is, almost all of the variation in sectoral share of employment is from differences across cohorts, rather than changes within cohorts across census years. This result lends strong support to the main thesis of this paper that structural change in response to trade liberalization is strongly driven by difference in sectoral share of employment across cohorts who joined the labor market after the trade liberalization relative to cohorts who joined the labor market earlier.

Migration: We now turn to age heterogeneity in prefecture-level migration in response to trade liberalization. Figure 1 shows share of workers in a prefecture who are migrants for each of cohorts born between 1935 and 2000. The figure presents migrant share weighted by number of workers in each cohort-prefecture cell. The figure clearly shows that there is a discontinuous jump in the share of migrant workers starting at cohorts born in 1985 and 1986. The share of workers who are migrants increased from approximately 27% for cohorts born in 1984 to nearly 45% for cohorts born in 1986.

We present the estimation results using across prefecture variation in exposure to and across cohort variation in responsiveness to trade liberalization in Table 4. Column (1) is based on data across census years aggregated to cohort-prefecture level (Equation (1)) whereas Column (2) conducts the estimation without aggregation across census years but instead includes census-year fixed effects (Equation (2)). The results across both columns show that migrant share of workers increases by 13 percentage points for cohorts born after 1986, relative to older cohorts, following one unit (100 percentage point) change in NTRgap. This result shows that most of the migration in response to decrease in tariff uncertainty is driven by the youth who just joined the labor market.

3 The model

This section develops a partial equilibrium model of migration to examine why younger cohorts respond more strongly to trade and industrial policy changes. By abstracting from general equilibrium effects—where wages, prices, and rents adjust endogenously—we can isolate the role of heterogeneous migration frictions across age cohorts.

Migration entails considerable income uncertainty, as individuals typically do not know their precise earnings at the destination with certainty. Instead, potential migrants base their decisions on the expected distribution of income, considering both its mean and variance, as well as their own risk preferences. In this environment, risk-averse individuals tend to avoid destinations with high income variance, all else equal, while more risk-tolerant individuals are more willing to accept such uncertainty. We hypothesize that older cohorts are more risk-averse than younger ones when responding to policy-induced economic opportunities. A central objective of this paper is to quantify the importance of this risk channel in shaping differential migration responses.

Several factors help explain why older individuals tend to exhibit greater risk aversion in migration decisions. First, older migrants are more likely to move with family members, for whom access to critical public services—such as education and healthcare—remains highly uncertain at the destination due to China's restrictive Hukou (household registration) system. In contrast, younger migrants are typically single and without dependents, and thus face considerably fewer constraints in this regard. Second, younger workers can expect a longer remaining working life at the destination. This extended time horizon allows potential gains from favorable wage realizations to accumulate over many years, making risk-taking more attractive. Older workers, with shorter expected tenure, stand to benefit from a high wage draw for a much briefer period, which reduces the incentive to accept income uncertainty. This generates risk-preference that endogenously vary with worker's life-span in a dynamic choice. (We demonstrate this latter by developing a dynamic model and showing how our approach in the main analysis provides a close approximation to this dynamic choice). Third, older workers have often accumulated substantial location-specific and sector-specific human capital, including professional networks and established career positions. Relocating therefore requires sacrificing these hard-earned advantages, raising the perceived cost of mobility, in particular when the earnings at the destination is uncertain. A young worker just entering the labor market, by comparison, has yet to build such ties and therefore faces a lower opportunity cost of moving to an uncertain outcome.

Together, these mechanisms generate systematically lower mobility frictions for younger cohorts, enabling them to respond more readily to new economic opportunities created by trade and industrial policies.

Suppose that an individual earns a random wage w_j at location j. A fraction β of this income is spent on consumption of goods with prices P_j and the remainder $1-\beta$ fraction is spent on housing with rent R_j. Real income of an individual who lives at location j can be written as $V_j = w_j/(P_j^{\beta} R_j^{1-\beta})$. Note that V_j is random because individuals do not certainly know the wage income they receive at destination location.

We assume that migrants have the following constant relative risk-aversion (CRRA) utility function

$$U_j = \frac{V_j^{1-\rho}}{1-\rho}, \quad \text{for} \quad \rho \neq 1 \tag{3}$$

where U_j is the indirect utility derived from real income at destination location and is a random variable. ρ is the *relative risk-aversion coefficient*. We allow this parameter to vary across cohorts (age-groups) without any restriction. If $\rho = 0$, the utility function becomes linear: $U_j = V_j$, indicating risk neutrality. If $\rho > 1$, the individual is highly risk-averse. If $\rho < 1$, the individual is less risk-averse.

Suppose V_j has a log-normal distribution $\ln(V_j) \sim N(\mu_j, \sigma_j^2)$. The expected utility function is given by:

$$E[U_j] = \frac{1}{1-\rho} \exp\left((1-\rho)\mu_j + \frac{1}{2}(1-\rho)^2\sigma_j^2\right) \tag{4}$$

Note that expected utility decreases with the variance of income distribution for risk-averse individuals. We find it convenient to work with the following certainty-equivalent representation of the expected utility:

$$\tilde{V}_j = \exp\left(\mu_j + \frac{1}{2}(1-\rho)\sigma_j^2\right) \tag{5}$$

where $\tilde{V}_j$ is the certainty-equivalent income for the random income V_j. For later use, it is useful to add location $\in \{i, j\}$, sector $\in \{k, l\}$ and cohort (or age) a indexes to the expected utility. Thus, the certainty-equivalent income from working in location j and sector l for a person with cohort (or age) a is written as $\tilde{V}_j^{a,l}$. For estimation of the model parameters, we use bilateral migration data for each cohort between sector-province pairs, i.e., (i, k) to (j, l). We define sectors broadly as agricultural and non-agricultural sectors following Tombe and Zhu (2019).

Migration decision: Given $\tilde{V}$, the individual makes migration decisions that maximizes its expected utility (more specifically, its certainty-equivalent income) net of migration costs and idiosyncratic location preferences. Suppose $C_{ij}^{a,kl}$ denotes utility cost of migrating from (i, k) to (j, l) for a person with age a. This is unobserved quantity and our goal is to estimate it. Workers have idiosyncratic destination preference ε_j^l with Fréchet distribution $F_\varepsilon(x) = e^{-x^{-\kappa}}$ where κ is a measure of dispersion of the distribution and governs migration elasticity.

An individual in location-sector (i, k) chooses location-sector (j, l) which maximizes its certainty-equivalent income net of utility cost of migration and idiosyncratic location preference, given the individual's risk preference:

$$\max_{j,l} \quad \left\{ \frac{\tilde{V}_j^{a,l} \varepsilon_j^l}{C_{ij}^{a,kl}} \right\} \tag{6}$$

Given the Fréchet distribution of ε_j^l, the probability of migration from (i,k) to (j,l) for a person with age a, $m_{ij}^{a,kl}$ is given by

$$m_{ij}^{a,kl} = \frac{\left(\tilde{V}_j^{a,l}/C_{ij}^{a,kl}\right)^{\kappa}}{\sum_{l'} \sum_{j'} \left(\tilde{V}_{j'}^{a,l'}/C_{ij'}^{a,kl'}\right)^{\kappa}} \quad \text{for} \quad (i,k) \neq (j,l) \tag{7}$$

The law of large numbers implies that $m_{ij}^{a,kl}$ is also the proportion of workers of age a migrating from (i,k) to (j,l). The number of workers of age a in destination j and sector l is given by $L_j^{a,l} = \sum_k \sum_i m_{ij}^{a,kl} L_i^{a,k}$.

The proportion of workers of age a who migrate from (i,k) to (j,l), $m_{ij}^{a,kl}$, relative to the proportion who stay at (i,k), $m_{ii}^{a,kk}$ is given by

$$\frac{m_{ij}^{a,kl}}{m_{ii}^{a,kk}} = \left(\frac{\tilde{V}_j^{a,l}}{\tilde{V}_i^{a,k} C_{ij}^{a,kl}} \right)^{\kappa}, \quad \text{for} \quad (i,k) \neq (j,l) \tag{8}$$

where $C_{ii}^{a,kk} = 1$ (i.e., stayers face no migration costs) has been used. Using Equation (5) in Equation (8) and taking logs gives

$$\ln \left(\frac{m_{ij}^{a,kl}}{m_{ii}^{a,kk}} \right) = \kappa \left(\mu_j^{a,l} - \mu_i^{a,k} \right) + 0.5\kappa(1-\rho^a) \left((\sigma_j^{a,l})^2 - (\sigma_i^{a,k})^2 \right) - \kappa \ln C_{ij}^{a,kl} \tag{9}$$

This equation has an intuitive interpretation. The first term implies that migration rate increases with average income at destination relative to average income at origin where κ measures elasticity of migration rates to average income differences between destination and origin location-sector cells. The second term implies that higher variance of income at destination relative to variance of income at origin location-sector cells causes more migration rate of individuals with $0 < \rho^a < 1$ but less migration rate of individuals with $\rho^a > 1$ (risk-averse individuals). The last term shows that migration rate decreases with bilateral migration costs. Our goal is to estimate the parameters κ and $\rho^a, \forall a$ that govern the migration friction.

3.1 Identification and estimation

To take the model to data, we assume moving costs between (i,k) and (j,l) for each age group a take the following form:

$$C_{ij}^{a,kl} = d_{ij}^{\theta}\tilde{\gamma}_i^k\tilde{\gamma}^a\tilde{\epsilon}_{ij}^{a,kl}, \quad \text{for} \quad (i,k) \neq (j,l) \tag{10}$$

where d_{ij} is bilateral distance and θ is the distance elasticity, $\tilde{\gamma}_i^k$ is origin i and sector k specific migration frictions that are constant across age and destinations included to capture asymmetric migration frictions between sectors and location, $\tilde{\gamma}^a$ is age specific migration frictions that are constant across origin-destination pairs, and $\tilde{\epsilon}_{ij}^{a,kl}$ is the residual which we assume is random.

Using Equation (10) in Equation (9), we have our main estimation equation:

$$\begin{aligned}\ln\left(\frac{m_{ij}^{a,kl}}{m_{ii}^{a,kk}}\right) &= \kappa\left(\mu_j^{a,l} - \mu_i^{a,k}\right) + \alpha^a\left((\sigma_j^{a,l})^2 - (\sigma_i^{a,k})^2\right) \\ &\quad + \theta\ln d_{ij} + \gamma_i^k + \gamma^a + \epsilon_{ij}^{a,kl}, \quad \text{for} \quad (i,k) \neq (j,l)\end{aligned} \tag{11}$$

where $\alpha^a \equiv 0.5\kappa(1-\rho^a)$, γ_i^k are origin-sector fixed effects and captures origin-sector specific unobserved factors common across all age groups, γ^a is cohort fixed effects capturing cohort-specific migration frictions and $\epsilon_{ij}^{a,kl}$ is a random error term. To check sensitivity of our results, we estimate the regression replacing bilateral distance by origin-destination pair fixed effects γ_{ij}.

The above regression equations suggest that there is potentially serious omitted variable bias when estimating migration elasticities based on models of migration that ignore migrants' risk preference. This is because these estimations omit the variance of income, which is correlated with the mean of income. To see this, note that variance of income $V = E[X^2] - E[X]^2$ is a function of its mean $E[X]$. Importantly, this bias cannot be addressed by the use of instrumental variables because any relevant instrument Z for the mean $(cov(E[X], Z) \neq 0)$ will fail the exclusion restriction $(cov(V, Z) \neq 0)$ because V is a function of $E[X]$.[8]

Identification issues: A potential identification issue in estimation of Equation (11) arises if unobserved factors correlated to income $(\mu_j^{a,l} - \mu_i^{a,k})$ influence migration flows. A good example is institutional quality and amenities at destination locations relative to origin location, which influence not only relative economic performances of locations but also influence individuals' migration decisions because people generally like to live in locations with better institutions and amenities. Similar endogeneity

[8]This correlation is zero for a normal distribution. However, for any other distribution this correlation is different from zero. For a lognormal distribution the correlation is positive. Income distribution is usually strongly positively skewed and it is best approximated by lognormal.

concern applies to the the second moment term in Equation (11) in the sense that locations with better institutions may have lower income uncertainty.

To address these endogeneity concerns, we use instrumental variables (IV) estimation strategy. We follow the literature and use population weighted average and variance of income of neighboring provinces to construct our IV. More specifically, we instrument $\left(\mu_j^{a,l} - \mu_i^{a,k}\right)$ by $\left(\sum_{j'} w_{j'}\mu_{j'}^{a,l} - \sum_{i'} w_{i'}\mu_{i'}^{a,k}\right)$ and $\left((\sigma_j^{a,l})^2 - (\sigma_i^{a,k})^2\right)$ by $\left(\sum_{j'} w_{j'}(\sigma_{j'}^{a,l})^2 - \sum_{i'} w_{i'}(\sigma_{i'}^{a,k})^2\right)$ where i' denotes the set of neighboring provinces to province i, j' denotes the set of neighboring provinces to province j and w denotes the population weights. A province's income is likely correlated to its neighbor's income as provinces with richer neighbors tend to be rich and provinces in the neighborhood of poorer provinces tend to be poorer. However, income of neighbors is likely exogenous to a given province's income and migration shocks.

Equation (11) can be estimated to obtain the key structural parameters κ and $\rho_a, \forall a$, given data on distribution of income in each age-sector-location cells. We use the 2005 mini-census data which includes information on workers' employment, migration, and wage income information to construct the mean and variance of wage in each age-sector-province cells. We use the same data to construct the dependent variable (proportion of migrants relative to stayers). We use provinces as geographic locations. Using lower-level geographic units such as prefectures poses the problem of too much sparseness in the bilateral migration data, given that our data is constructed at location-sector-age cell level. Using provinces as geographic units overcomes this problem.

3.2 Results

3.2.1 Migration elasticity and risk parameters

We present our main estimation results in Table 5. Column (1) of the table presents results for our main estimation Equation (11) while Column (2) replaces bilateral distance by origin-destination pair fixed effects. Both columns present IV estimation results.

The first row in Table 5 presents the estimated value of κ, the elasticity of migration to mean income gap between destination and origin provinces. In our preferred specification that includes bilateral distance in Column (1), the value of this parameter is 3.9. Replacing the bilateral distance by province-pair fixed effects in Column (2) slightly decreases this parameter to 3.5. The value of κ we estimate is slightly larger than those reported in previous studies including (Tombe and Zhu, 2019; Bryan and Morten, 2019). Bryan and Morten (2019) obtain $\kappa = 2.7$ for the U.S and 3.2 for Indonesia while Tombe and Zhu (2019) find values in the range of 1.2-1.6 for China. However, as the discussion above suggests, ignoring risk preference would generally cause underestimation of κ if migrants are risk-averse on average. Our results confirm this.

Table 5 also reports the elasticity of migration to difference in income variance between destination and origin provinces ($\alpha^a \equiv 0.5\kappa(1-\rho^a)$) for each age cohorts. We use the 60-64 cohort as base group for our estimation. For this group, the elasticity of migration to income variance is -2.8. For those aged 45-49 this elasticity is -0.83 (i.e., -2.8+1.97). For the youth aged 15-19, this elasticity is 2.1 (positive), implying that this group would like to migrate to provinces with higher income variance. Overall, the elasticity of migration flow to income variance tends to monotonically decrease across ages.

The elasticity of migration flow to differences in mean and variance of income between destination and origin locations govern migrants' risk preference. The risk preference parameter for each cohort can be recovered as $\rho^a = 1 - (2 * \alpha^a)/\kappa$. Table 6 reports the values of these parameters along with their bootstrap standard errors. The two panels in Table 6 report risk preference parameters corresponding to each column in Table 5. Across both panels, we observe that the estimated risk parameters are the lowest for the youngest cohorts (with $\hat{\rho} \approx -0.1$) and the highest for the oldest cohorts (with $\hat{\rho} \approx 3.9$). In other words, the oldest cohorts are the most risk-averse while the youngest are the least risk-averse. In fact, the risk preference parameter for cohorts aged 15-19 reflects that this group are slightly risk-loving. Overall, the degree of risk-aversion tends to increase monotonically with age. These results are robust across all our sensitivity analysis.

The estimated risk preference parameters suggest that migrants are risk-averse, on average. As a result, models of migration that ignore migrants risk preferences would underestimate the elasticity of migration to income difference, which biases the estimated migration costs.

3.2.2 Migration costs

Using our estimated values of κ and the cohort-specific risk preference ρ^a, we compute the migration costs between province-sector pairs $(i,k) \neq (j,l)$ for each cohort as follows:

$$C_{ij}^{a,kl} = \left(\frac{m_{ii}^{a,kk}}{m_{ij}^{a,kl}}\right)^{1/\kappa} e^{(\mu_j^{a,l} - \mu_i^{a,k}) + 0.5(1-\rho^a)((\sigma_j^{a,l})^2 - (\sigma_i^{a,k})^2)} \tag{12}$$

To ease interpretation, we normalize this measure by the destination utility, $e^{\mu_j^{a,l} + 0.5(1-\rho^a)\sigma_j^{2,a,l}}$ so that migration costs are expressed relative to worker's current utility at the destination.

The results are reported in Table 7. Column (1) presents the average migration costs between different province-sector pairs $i \neq j, k \neq l$. The estimated average migration costs range from 2.2 for the youngest cohorts aged 15-19 to 27.7 for the oldest cohorts aged 60-64. Overall, the migration costs tend to increase with ages of cohorts. The large average migration costs are partly driven by high migration costs (low migration flows) between some province-sector pairs. The median migration costs are smaller than the average costs as shown in Table 9 but show the same pattern across cohorts as the average migration costs.

Columns (2)-(5) present the average migration costs between different provinces for different sectoral paths. Column (2) shows migration costs from agriculture (A) to non-agriculture (NA) across provinces while Column (3) reports migration in the opposite direction. Column (4) shows migration within agricultural sector between different provinces while Column (5) shows migration within non-agricultural sector across provinces. There are a number results worth emphasizing. First, bilateral migration costs across provinces between agriculture and non-agriculture are not symmetric. Across provinces, migration from agriculture to non-agriculture is more costly compared to the costs of migration in the opposite direction. Second, inter-provincial migration within the agricultural sector involve the highest migration costs; in particular they are higher than inter-provincial migration costs in the non-agricultural sector. This is consistent with the Chinese land tenure system acting as a barrier to farmers' migration across provinces (see, for instance, Adamopoulos et al. (2024)). Third, inter-provincial migration costs generally increase with age of cohorts regardless of the origin and destination sectors.

Columns (6)-(7) report within province migration costs between different sectors (i.e., costs of switching sectors within the same province). These costs are about one-tenth of inter-provincial migration costs. Switching from agriculture to non-agriculture involves slightly higher costs than the move in the opposite direction, particularly for the older cohorts. Similar to inter-provincial migration costs, costs of switching sectors within a province significantly rise with cohort ages.

Next, we explore how the estimated migration costs vary with distance. Table 8 reports the elasticity of migration costs to distance of 1.35 when migration costs are estimated allowing risk parameters to vary across cohorts. This elasticity is 0.92 for migration costs estimated by imposing risk neutrality on all cohorts (see below).

3.2.3 The role of risk preference

To quantify the extent to which age-related increases in migration costs are driven by shifting risk preferences, we conduct a counterfactual analysis. Specifically, we evaluate how the distribution of migration costs would vary across cohorts if all cohorts shared an identical risk parameter, $\rho^a = 0$ for all a [9]. Under this assumption of risk neutrality, the migration cost is defined as: $\left(\frac{m_{ii}^{a,kk}}{m_{ij}^{a,kl}}\right)^{1/\kappa} e^{(\mu_j^{a,l}-\mu_i^{a,k})+0.5(\sigma_j^{2,a,l}-\sigma_i^{2,a,k})}$. By comparing these counterfactual estimates against our baseline costs—which incorporate cohort-specific risk preferences as defined in Equation (12)—we can isolate the impact of risk attitudes. This decomposition allows us to determine the proportion of age-based variation in migration costs that is fundamentally driven by a cohort's changing sensitivity to income volatility at the destination.

The results, presented in Figure 3, reveal a stark contrast between migration costs calculated with a constant risk parameter versus those allowing for variable risk preferences. While costs associated with a constant risk parameter remain relatively flat across age cohorts, those accounting for heterogeneous risk preferences exhibit significant variation. This pattern holds across most migration pathways, whether intra- or inter-provincial. Figure 4 further illustrates the heterogeneous impact of risk preferences on the monotonicity of migration costs across different paths. Notably, migration costs for workers leaving the non-agricultural sector demonstrate a higher sensitivity to risk preferences compared to those originating from agriculture.

The left column of Figure 4 (Panels (a)–(c)) focuses on migrants from the agricultural sector. For this group, migration costs rise with cohort age when risk preferences are allowed to vary; however, this age-based increase is significantly subdued when the risk parameter is held constant.

The right column (Panels (d)–(f)) provides even more compelling evidence for migrations originating from the non-agricultural sector. Here, the observed monotonicity of migration costs relative to cohort age appears to be primarily driven by variations in the degree of risk aversion. This is evidenced by the fact that while migration costs are strictly monotonic with age under variable risk parameters, they become essentially flat across all cohorts when a constant risk-preference parameter is imposed. These findings suggest that the perceived "cost" of migration for older cohorts is significantly amplified by their heightened sensitivity to income risk at destination locations.

3.3 Alternative specification

As a robustness exercise, we estimate our migration equation using destination-level variation only:

$$\ln\left(\frac{m_{ij}^{a,kl}}{m_{ii}^{a,kk}}\right) = \kappa\mu_j^{a,l} + \alpha^a(\sigma_j^{a,l})^2 + \gamma_{ij} + \gamma_i^k + \gamma_i^a + \epsilon_{ij}^{a,kl}, \quad \text{for} \quad (i,k) \neq (j,l) \qquad (13)$$

[9] Adopting an alternative constant value for ρ would shift the absolute level of estimated costs uniformly without altering the underlying cross-cohort comparative analysis.

The only difference between the current regression and our baseline regression is that in the baseline regression the independent variables are differences in the mean and variance of income between destination and origin locations while in the current regression the regressors are mean and variance of income at destination location. Given our origin-sector fixed effects in the regressions, these two regressions are closely related. We instrument $\mu_j^{a,l}$ by $\sum_{j'} w_{j'}\mu_{j'}^{a,l}$ and $(\sigma_j^{a,l})^2$ by $\sum_{j'} w_{j'}(\sigma_{j'}^{a,l})^2$, respectively, where j' denotes the set of neighboring provinces to province j and w denotes the population weights.

We present the results in Table A.1. Column 1 presents results with origin-destination pair fixed effects while Column 2 replaces the fixed effect with log distance between origin and destination provinces. The results are similar across both columns. Moreover, the results in this table are very similar to their counterparts in our main analysis, showing that our conclusions are not sensitive to changes in our regression specifications. The first row in Table A.1 reports the elasticity of migration flow with respect to average income at destination. The reported elasticities ranging from 3.5-3.9 are very similar to their counterparts in Table 5. Moreover, the elasticity of migration flows with respect to variance of income at destination reported in Table A.1 are similar to their counterparts in the main analysis. In particular, these elasticities significantly decrease with age of cohorts.

Table A.2 reports the resulting risk preference parameters across age cohorts. Similar to the results in the main analysis, the new estimates show that the youngest cohorts have the lowest risk parameter while the oldest cohorts have the highest risk parameter. Moreover, the youngest cohorts (aged 15-19) have a risk parameter below one. All the other age cohorts have risk parameter larger than one, suggesting that they are risk averse.

We report the migration costs corresponding to the new parameters in Table A.3. These migration costs have similar features as those in the main analysis. First, they are lowest for the youngest cohorts and highest for the oldest. They generally increase with age of the cohorts. Second, migration costs are higher for migrants originating from the agricultural sector compared to those originating from non-agriculture. Third, inter-province migration costs are about ten times larger than costs of switching sectors within a province. Overall, the results in this table reinforce our results in the main analysis[10].

[10] The similarities with the main result are partly driven by the origin province-sector and origin province-cohort fixed effects included in both regressions.

4 Extension: Nested migration model

In this section, we extend the above migration model to a nested structure to account for the possibility that workers' choices of destinations are nested by geography and sector. We hypothesize that a worker first selects a destination province j and subsequently chooses a sector l within that province.

The Hukou system serves as the institutional foundation for our nested approach. It creates a 'tier' of migration costs where the elasticity of substitution across regions (κ_r) is constrained by policy-induced frictions (loss of access to public services and legal status), while the elasticity across sectors (κ_s) within a region is primarily constrained by human capital. Our main analysis above reveals that inter-provincial migration costs are significantly higher than the costs of switching sectors with in a province, implying $\kappa_s > \kappa_r$. By assuming identical elasticity for both types of migration our baseline model would over-predict inter-provincial migration by ignoring the workers' preferences for staying within one's Hukou-authorized region. The nested model allows for higher correlation between choices within the same province, reflecting the reality that sectoral mobility within a region is a closer substitute than inter-provincial migration.

To obtain the nested model, we assume the idiosyncratic preference shocks ε_j^l follow a Nested Fréchet Distribution, allowing for correlation among sectors within the same geographic region:

$$F(\{\varepsilon_j^l\}) = \exp\left[-\sum_j \left(\sum_l (\varepsilon_j^l)^{-\kappa_s}\right)^{\frac{\kappa_r}{\kappa_s}}\right] \tag{14}$$

where κ_s is the elasticity of migration across sectors (within a region) and κ_r is the elasticity of migration across regions. Consistency requires $\kappa_s \geq \kappa_r$ (though we do not impose this in our estimation). With nested Fréchet distributed idiosyncratic shocks, the probability $m_{ij}^{a,kl}$ is decomposed into the product of the probability of choosing destination j and the conditional probability of choosing sector l given destination j:

$$m_{ij}^{a,kl} = \underbrace{\frac{(\mathcal{I}_{ij}^a)^{\kappa_r}}{\sum_{j'}(\mathcal{I}_{ij'}^a)^{\kappa_r}}}_{\text{Probability of choosing province } j} \times \underbrace{\frac{(\tilde{V}_j^{a,l}/C_{ij}^{a,kl})^{\kappa_s}}{\sum_{l'}(\tilde{V}_j^{a,l'}/C_{ij}^{a,kl'})^{\kappa_s}}}_{\text{Probability of choosing sector } l \text{ given province } j} \tag{15}$$

where $\mathcal{I}_{ij}^a$ is the overall attractiveness of destination j for a worker from origin i:

$$\mathcal{I}_{ij}^a = \sum_k \left[\sum_{l'} \left(\frac{\tilde{V}_j^{a,l'}}{C_{ij}^{a,kl'}}\right)^{\kappa_s}\right]^{1/\kappa_s} \tag{16}$$

Suppose the migration cost $C_{ij}^{a,kl}$ is separable and takes the following functional form:

$$C_{ij}^{a,kl} = d_{ij}^{\theta}\tilde{\gamma}^{kl}\tilde{\gamma}^{a} \tag{17}$$

where d_{ij}^{θ} represents bilateral geographic frictions, $\tilde{\gamma}^{kl}$ denotes sector-switching costs, and $\tilde{\gamma}^{a}$ is a cohort-specific baseline migration cost. The explicit expression for the ratio of workers of age a moving from origin (i,k) to destination (j,l), relative to those staying at (i,k), is:

$$\frac{m_{ij}^{a,kl}}{m_{ii}^{a,kk}} = \left(\frac{\tilde{V}_j^{a,l}/(d_{ij}^{\theta}\tilde{\gamma}^{kl}\tilde{\gamma}^{a})}{\tilde{V}_i^{a,k}}\right)^{\kappa_s} \times \left[\frac{\Gamma_j^{a,k}/(d_{ij}^{\theta}\tilde{\gamma}^{a})}{\Gamma_i^{a,k}}\right]^{\kappa_r-\kappa_s} \tag{18}$$

where $\Gamma_j^{a,k}$ is the attractiveness of province j to workers from sector k [11]:

$$\Gamma_j^{a,k} = \left[\sum_{l'}\left(\frac{\tilde{V}_j^{a,l'}}{\tilde{\gamma}^{kl'}}\right)^{\kappa_s}\right]^{1/\kappa_s} \tag{19}$$

Taking the natural log of Equation (18) yields the linear estimation equation:

$$\begin{aligned}\ln\left(\frac{m_{ij}^{a,kl}}{m_{ii}^{a,kk}}\right) &= \kappa_s(\mu_j^{a,l}-\mu_i^{a,k}) + \frac{\kappa_s(1-\rho_a)}{2}((\sigma_j^{a,l})^2-(\sigma_i^{a,k})^2) \\ &\quad - \kappa_r\theta\ln d_{ij} + \tilde{\gamma}^{kl} + \tilde{\gamma}^{a} + (\kappa_r-\kappa_s)\left(\ln\Gamma_j^{a,k}-\ln\Gamma_i^{a,k}\right)\end{aligned} \tag{20}$$

Compared to our main model, in this specification migration flow also depends on the attractiveness of the destination location relative to the attractiveness of the origin for workers from the same sector (the last term in the above equation). Omitting this term results in biased estimates as this term is correlated with wages and geographic distance. The term has similar interpretations as amenities of the destination relative to origin.

The coefficient on the mean income difference identifies the sectoral elasticity κ_s, while the coefficient on bilateral distance identifies the regional elasticity scaled by the distance parameter, $\equiv \kappa_r\theta$. Finally, ρ^a is identified from the combinations of the coefficient of income variance difference and κ_s. In the remaining part of the paper, we assume $\theta = 1$ because we cannot separately identify this parameter.

Estimation: Estimation of the above equation is slightly complicated compared to our baseline model due to the last term in the equation. To account for this term, we follow an iterative procedure where we first guess the initial values of parameters (κ_s, κ_r, ρ^a, and $\tilde{\gamma}^{kl}$) and construct the corresponding $\left(\ln\Gamma_j^{a,k}-\ln\Gamma_i^{a,k}\right)$. We than include

[11]The overall attractiveness of province j to workers from province i is $\mathcal{I}_{ij}^{a} = d_{ij}^{-\theta}\tilde{\gamma}^{-a}\sum_k\Gamma_j^{a,k}$.

this in our IV estimation of the above migration equation to obtain updated value of the model parameters. We instrument the mean and variance income differences between destination and origin using the same set of IVs introduced in our main analysis. We iterate this procedure until the parameters become stable. Details of the estimation procedure are provided in Appendix C.

Recovering migration costs: We calculate migration costs as

$$C_{ij}^{a,kl} = \left(\frac{m_{ii}^{a,kk}}{m_{ij}^{a,kl}}\right)^{1/\kappa_s} \exp\left[(\mu_j^{a,l} - \mu_i^{a,k}) + \frac{1-\rho^a}{2}((\sigma_j^{a,l})^2 - (\sigma_i^{a,k})^2) + \left(\frac{\kappa_r - \kappa_s}{\kappa_s}\right)\ln\left(\frac{\Gamma_j^{a,k}}{\Gamma_i^{a,k}}\right)\right]$$

We normalize this by the workers' current utility $\exp(\mu_j^{a,l} + 0.5(1-\rho^a)(\sigma_j^{a,l})^2)$ so that the migration costs are interpreted relative to workers' current utility.

4.1 Results

Table 10 reports the parameter estimates for the nested model, with standard errors derived via bootstrapping with 50 replications. The first two rows display the migration elasticity parameters. In line with our theoretical framework, the results indicate that $\hat{\kappa}_s = 3.5$, which significantly exceeds $\hat{\kappa}_r = 1.5$. This disparity implies that labor is more elastic across sectors than across provinces, a finding that remains consistent with the observation that inter-provincial migration costs are substantially higher than the costs of switching sectors within a single province.

The subsequent rows detail the risk-aversion parameters (ρ) by age group. These estimates align closely with those obtained in our primary analysis. Specifically, the youngest cohort (ages 15–19) exhibits a risk-aversion parameter of zero, indicating risk neutrality. For all older cohorts, the parameter is greater than or equal to one and generally increases with age, culminating in a parameter of 2.12 for the 60–64 age group. This trend reflects a high degree of risk aversion in older cohorts relative to their younger counterparts.

Figures 5 and 6 illustrate the implied migration costs. As shown in Figure 5, total migration costs mirror the magnitudes found in our main analysis and exhibit a clear upward trajectory over the life cycle. Notably, a counterfactual scenario where all workers are risk-neutral reveals that migration costs would remain relatively flat across most cohorts, with the exception of the oldest age group.

To further investigate these frictions, Figure 6 disaggregates migration costs by specific mobility paths. The results reveal that inter-provincial migration costs are approximately tenfold higher than the costs associated with intra-provincial sectoral switching. For workers originating in the non-agricultural sector, age-based heterogeneity in migration costs is largely driven by differences in risk attitudes;

under the assumption of risk neutrality, migration costs for these workers would be both modest in scale and uniform across age groups. Conversely, risk aversion plays a negligible role in explaining the high migration costs faced by older cohorts originating from the agricultural sector. This finding deviates from our baseline results and warrants a cautious interpretation regarding the structural barriers unique to agricultural labor. Ultimately, the nested model produces migration costs that are remarkably consistent with our main analysis in both level and pattern, reinforcing the robustness of our structural estimates.

5 Migration costs from survey reports

In this section, we validate our model-based estimates by comparing them against self-reported migration costs from the 2007 China Household Income Project (CHIP) survey. The CHIP dataset provides a unique opportunity to elicit costs directly, as it records both the current earnings of migrant households and their counterfactual income—the earnings they estimate they would have received had they remained at their origin. Using these data, we define migration costs as the ratio of current income to counterfactual origin income, aggregated by age group.

As illustrated in Figure 7, the self-reported migration costs are systematically lower than our structural estimates. This discrepancy is theoretically consistent with a classic selection bias: self-reported data are inherently conditional on the decision to migrate. Because the survey only captures individuals who found it profitable to move, it likely reflects a lower-bound of the migration frictions present in the general population. Those who remained at their origin presumably faced significantly higher costs that deterred relocation. Our model-based approach explicitly accounts for this selection issue, which explains why our estimated frictions are larger in magnitude.

Despite the difference in levels, the survey-based costs exhibit a life-cycle pattern that closely mirrors our model's results. The self-reported costs are lowest for the youngest cohort (ages 15–19) and rise sharply through the 35–39 age group, where costs are approximately 70% higher than for the youngest workers. While the survey data show a slight decline in costs after the 40–44 age group, our model-based estimates continue to rise. We attribute this divergence to a worsening of the selection bias among older cohorts, who may require even higher potential gains or lower idiosyncratic costs to justify migrating late in their careers. Taken together, these self-reported figures provide strong empirical reinforcement for the age-dependent patterns identified in our structural analysis.

6 Relationship to dynamic life-cycle model

We view our approach of exogenous age gradient in risk aversion as an approximation to an endogenous life-cycle horizon (life-span) effect in a dynamic programming problem with a finite horizon T. In the dynamic setup, consider the case where risk aversion parameter is constant across all ages. Younger agents with age a will naturally exhibit a higher willingness to move to high-risk, high-return locations because they have a longer remaining working lifespan $(T - a)$ to absorb economic shocks and capitalize on the "option value" of a high-return market. This results in effective risk-aversion increase with age. Here we provide a simplified framework to formalize this intuition and demonstrate the close connection with our static model with exogenous age gradient in risk-aversion.

Suppose an individual lives for a finite number of periods, $t = 1, 2, \ldots, T$. At any age a, the remaining working lifespan is $T - a$. For simplicity, we assume no discounting to keep the horizon effect as transparent as possible. There are two locations: Origin (o) which we assume is a safe, low-return location and yields a deterministic wage w_o every period; and destination (d) which we assume is a risky, high-return location. In any period, it yields a stochastic wage $\tilde{w}_d$. To capture the risk, let $\tilde{w}_d = w_d + \epsilon_{dt}$, where $w_d > w_o$ (higher expected return), and ϵ_{dt} is an i.i.d. shock across years with $\mathbb{E}[\epsilon_{dt}] = 0$ and variance σ_d^2.

Let's write our period utility generally as $u(w)$ and migration from o to d incurs a one-time, deterministic moving cost, C. Because the destination is risky but has a higher mean, the timing (age) of migration matters. We can analyze this through two complementary perspectives: option value and shock-smoothing channels. Here we develop the option value channel in more detail and provide the high light of the shock-smoothing channel, as modeling the two mechanisms is very similar in structure.

To demonstrate that the option value of being in a high-return location is greater the longer you stay, let's assume income draws are persistent or reveal a permanent match quality, making migration an investment. Suppose when an agent moves to d, they permanently draw a career path: either it's a "good match" (w_d^g) or a "bad match" (w_d^b). They learn the truth after one period. If it's a bad match, they can always choose to move back to o next period (incurring another cost, or zero cost to return home). The value of migrating to d at age a, $V_{migrate}(a)$, is:

$$V_{migrate}(a) = \mathbb{E}[u(\tilde{w}_{d,a})] - C + \sum_{t=a+1}^{T} \mathbb{E}\left[\max\{V_d^{match}(t), V_o(t)\}\right] \tag{21}$$

Intuitively, if a young person moves at $a = 20$ and discovers a bad match, they lose C and one period of low utility, but they still have $T - 21$ periods to return home or try something else. If it's a good match, they reap the premium $(w_d^g - w_o)$ for decades. If an older person moves at $a = T - 2$, they pay the exact same upfront cost C, but they only get to enjoy the good match upside for 2 periods. The fixed cost C dominates the truncated future gains.

A worker decides to migrate if: $V_{migrate}(a) > V_{stay}(a)$. Using a Taylor expansion approximation of the value functions (detail of the derivation are given in the appendix), the net benefit of migration at age a can be written as a function of the remaining time horizon:

$$\text{Net Benefit} \approx (T - a)(w_d - w_o) - \frac{1}{2}\gamma(T - a)\sigma_d^2 - C \tag{22}$$

where $\gamma = -\frac{u''(w_d)}{u'(w_o)}$ is risk-aversion parameter (assuming evaluating marginal utilities across the baseline wages is close to a constant local risk aversion factor), and $\gamma(T - a)$ is the effective risk aversion mapped out by the remaining horizon. If $\gamma > 0$ effective risk-aversion rises with age. If $\gamma < 0$ effective risk-loving decreases with age. Intuitively, the returns to the variance change behavior entirely because longer horizons make agents risk-loving over the upside choice (the max operator is convex).

Equation (22) is closely related to our migration equation in (9). The main difference lies in the horizon multiplier $(T - a)$ scales both the the expected wage differences and the structural risks. A more general version of our migration equation allows κ to vary with age, making the comparison with Equation (22) even more close. In our estimation, we restrict κ to be constant across age for two reasons. First, we do not see significant variation in estimated values of κ across ages. Second, allowing both κ and ρ to vary freely across age causes practical estimation challenges when IV estimation strategy is used.

The shock-smoothing channel gives similar decision rule where effective risk aversion rises with age because asset smoothing windows contract with age. To model the mechanism that young people have more time to "smooth out" bad draws, we allow agents to borrow and save using an asset A_t at a risk-free rate r. The value function in the destination d at age a is:

$$V_d(A_a, a) = \max_{A_{a+1}} \left\{ u(A_a(1 + r) + \tilde{w}_{d,a} - A_{a+1}) + \mathbb{E}_a \left[V_d(A_{a+1}, a + 1) \right] \right\} \tag{23}$$

subject to the terminal condition $V_d(A_{T+1}, T+1) = 0$. This gives similar approximate net benefit equation as above. Intuitively, a young worker (low a, large $T - a$) who receives a negative shock ϵ can smooth consumption by borrowing against a long stream of future high expected wages (w_d). An older worker (high a, small $T - a$) cannot borrow as effectively because they must repay the debt quickly before retirement. Thus, a negative shock translates directly into a painful consumption drop today. Even with identical $u(\cdot)$, older workers fear the variance σ_d^2 more because their self-insurance capacity shrinks with age.

To sum up, while we treat the age gradient in the risk-aversion parameter as exogenous in our main analysis, we show that it can be generated endogenously in a dynamic choice problem with life-span effect. Indeed, our estimation equation can be considered as an approximation of the migration rule from the dynamic choice problem.

7 Conclusion

This paper examines how workers' responses to trade and industrial policy shocks—through migration and sectoral reallocation—differ systematically across age cohorts. Our findings reveal that younger workers drive the vast majority of both geographic and sectoral adjustments. They enter expanding sectors and regions in disproportionately large numbers, accounting for most of the observed labor reallocation.

We show that this pattern arises from substantial heterogeneity in mobility frictions across age groups, primarily driven by differences in attitudes toward income risk. Younger cohorts, especially those who have recently entered the labor market, exhibit significantly lower risk aversion. As a result, they are far less deterred by the uncertainty of potential income losses at new destinations or sectors compared to their older counterparts.

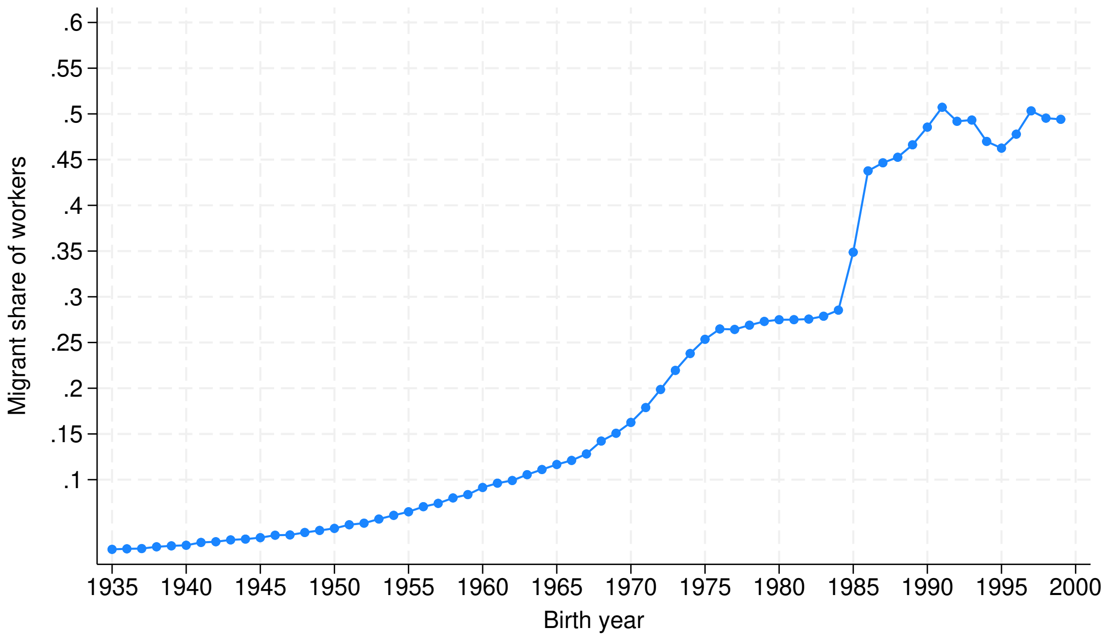
Our analysis further demonstrates that the costs of migrating across provinces are substantially higher than the costs of switching sectors within the same province. Moreover, income risk influences these costs asymmetrically: risk aversion plays a smaller role in deterring moves from agriculture to non-agricultural sectors than in discouraging the reverse transition.These results carry important policy implications for structural transformation and economic development. Whether labor reallocation is achieved primarily through existing workers switching sectors and locations, or through new labor market entrants disproportionately joining booming sectors and regions, has profound consequences for policy design. While such reallocations are essential for sustained growth, the precise barriers impeding them have remained insufficiently understood. In particular, policymakers in developing countries—especially in Sub-Saharan Africa—must determine whether structural change is constrained more by high mobility frictions facing workers or by the slow expansion of modern, high-productivity sectors capable of absorbing labor.

The Chinese experience analyzed in this paper offers a compelling lesson: even stringent, state-imposed mobility barriers such as the hukou system only modestly delay, but do not prevent, large-scale sectoral and geographic reallocation. Because mobility frictions are markedly lower for young workers entering the labor market, this demographic group alone can generate substantial structural transformation. Consequently, countries with youthful demographics that successfully foster the rapid growth of modern manufacturing and service sectors can achieve rapid labor reallocation—even in the presence of significant mobility barriers. In this light, China's dramatic trade liberalization of the 1990s and 2000s likely produced faster reallocation than it would have if implemented today, given the country's now older age structure.

Overall, our study highlights that a young and dynamic workforce can serve as a powerful engine of structural change, helping economies overcome barriers that might otherwise appear insurmountable.

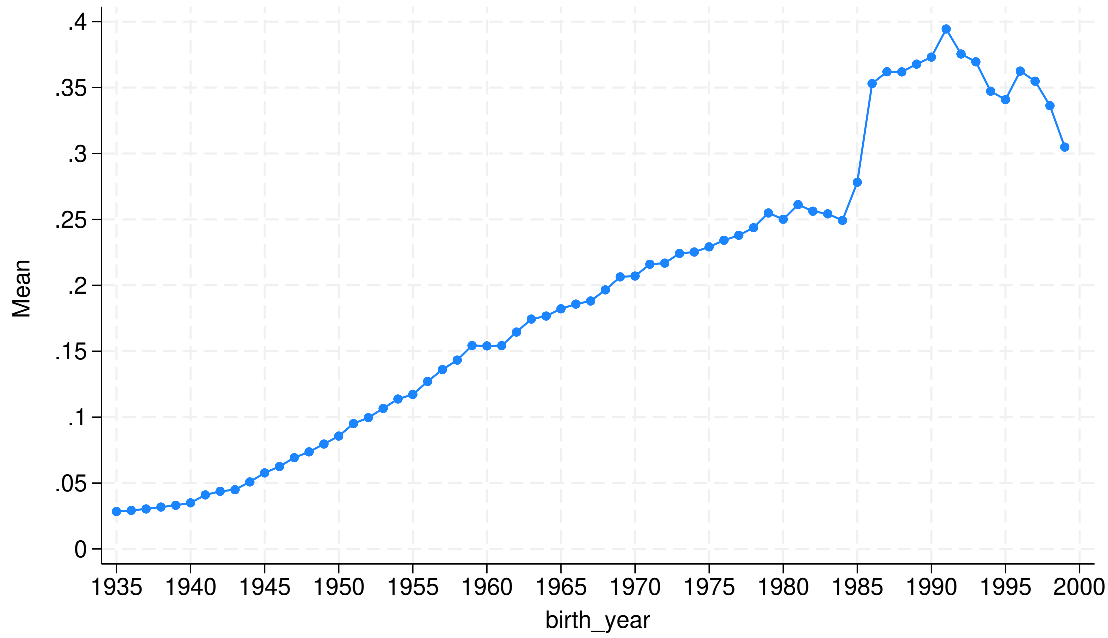
Figures

Figure 1: Share of migrant workers across cohorts (weighted by number of workers)



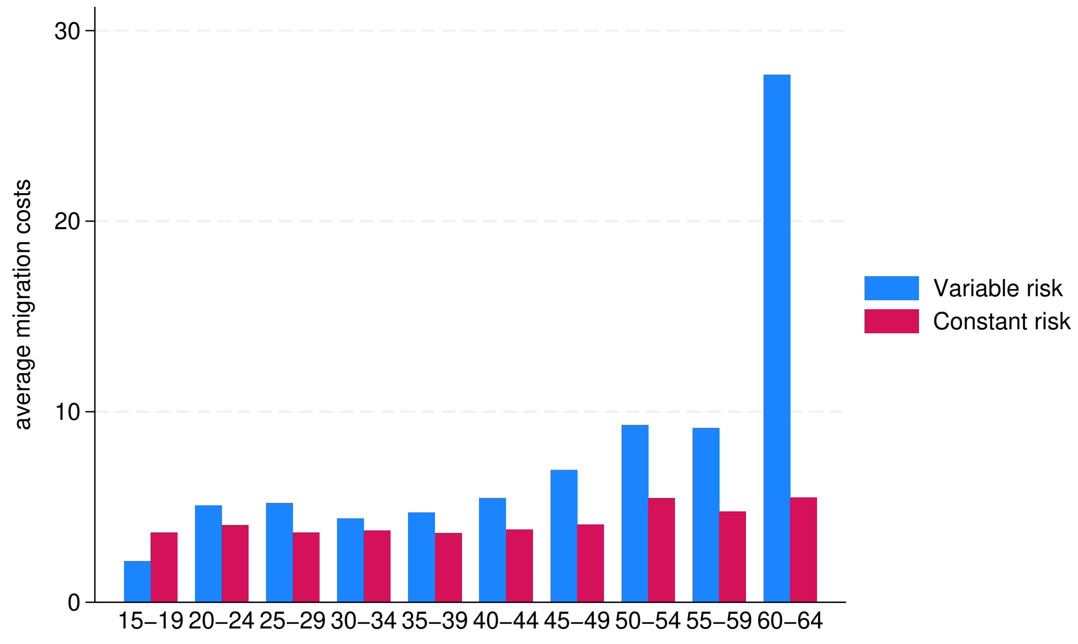
Notes: This figure plots the average share of migrants workers in Prefectures across cohorts. The number of workers in each prefecture is used as weights in calculation of the national average.

Figure 2: Share of employment in the secondary sector across cohorts



Notes: This figure plots the average share of employment in the manufacturing sector in Prefectures across cohorts.

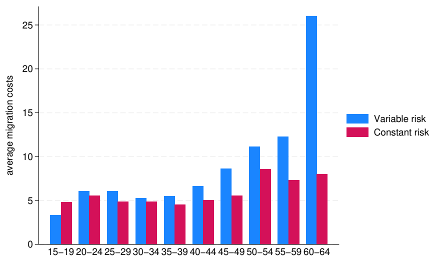
Figure 3: Migration costs when risk parameter varies vs when it is constant across cohorts ($\rho^a = 0, \forall a$)



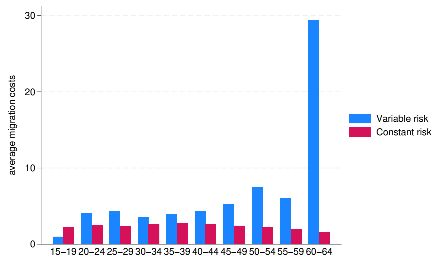
Notes: This figure shows variation of migration costs with cohort age. Migration costs are calculated under two scenarios:(i) using empirically estimated risk parameters varies across cohorts and (ii) assuming a uniform risk parameter across cohorts ($\rho^a = 0, \forall a$).

Figure 4: Migration costs across different paths when risk parameter varies across cohorts vs when it is assumed to be constant ($\rho^a = 0, \forall a$)

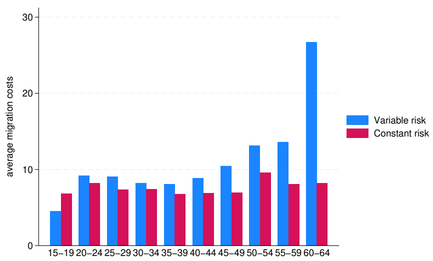
(a) Inter-province Ag $\rightarrow$ Na



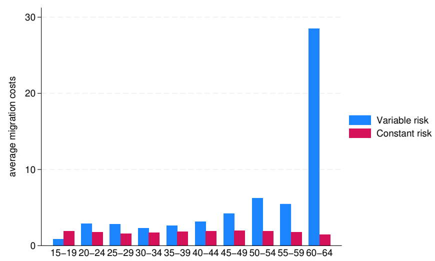
(d) Inter-province Na $\rightarrow$ Ag



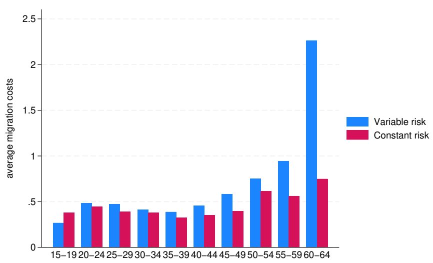
(b) Inter-province Ag $\rightarrow$ Ag



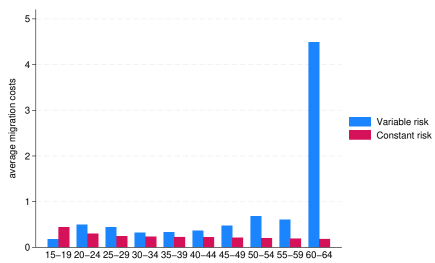
(e) Inter-province Na $\rightarrow$ Na



(c) Intra-province Ag $\rightarrow$ Na

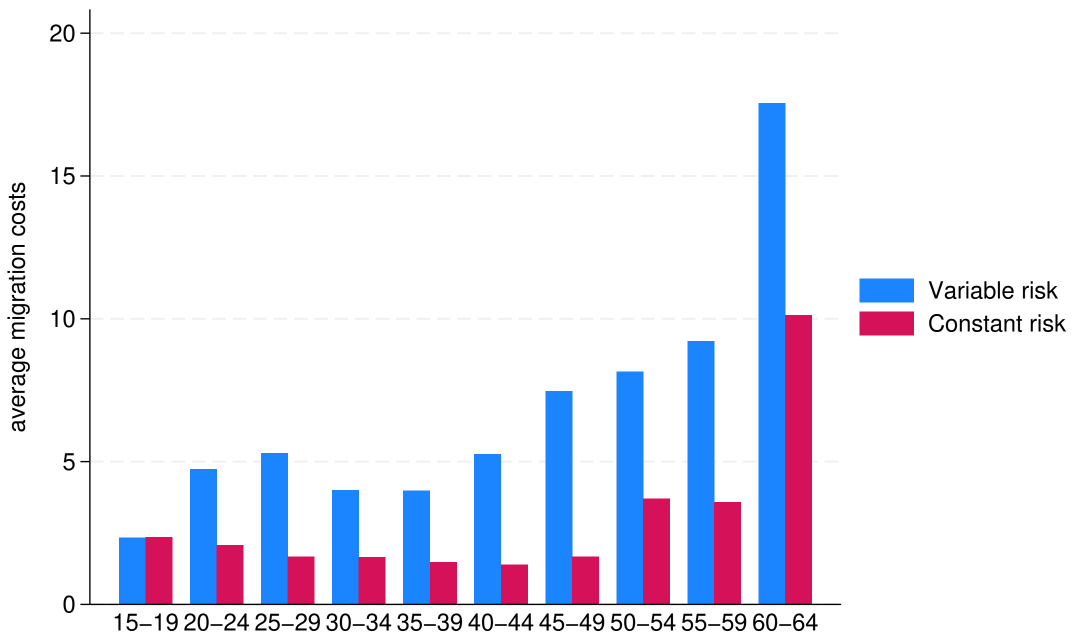


(f) Inta-province Na $\rightarrow$ Ag



Notes: The figures present estimated migration costs across cohorts for different migration paths under two scenarios: (i) under observed risk parameter of each cohort and (ii) assuming all cohorts have the same risk preference parameter ($\rho^a = 0, \forall a$). Panels (a)-(c) present migrations originating from agriculture. Panels (d)-(f) present migrations originating from non-agriculture. Panels (c) and (f) present the costs of switching sectors within a province. Migration costs are measured relative to destination utility.

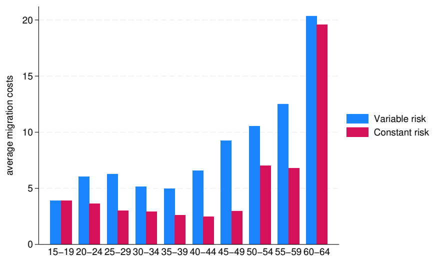
Figure 5: Nested migration costs when risk parameter varies vs when it is constant across cohorts ($\rho^a = 0, \forall a$)



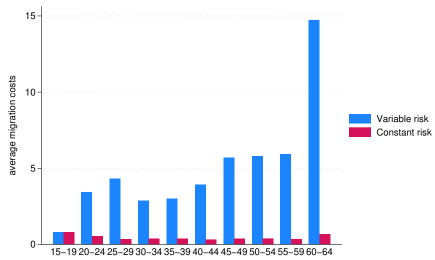
Notes: This figure shows variation of nested migration costs with cohort age. Migration costs are calculated under two scenarios:(i) using empirically estimated risk parameters varies across cohorts and (ii) assuming a uniform risk parameter across cohorts ($\rho^a = 0, \forall a$).

Figure 6: Nested migration costs across different paths when risk parameter varies across cohorts vs when it is assumed to be constant ($\rho^a = 0, \forall a$)

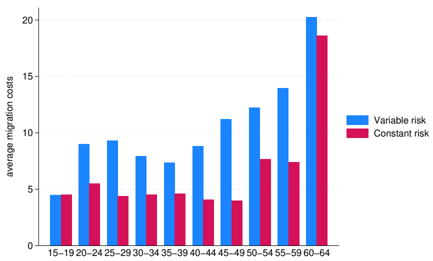
(a) Inter-province Ag $\rightarrow$ Na



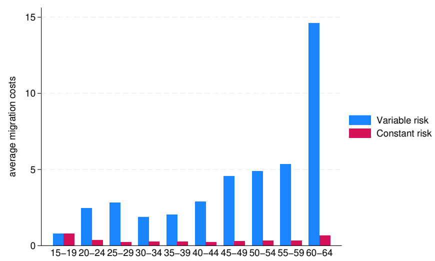
(d) Inter-province Na $\rightarrow$ Ag



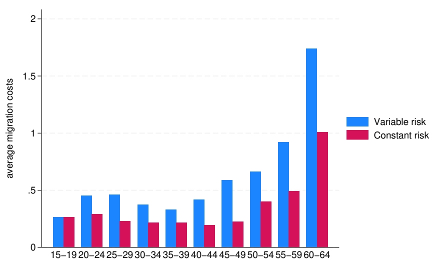
(b) Inter-province Ag $\rightarrow$ Ag



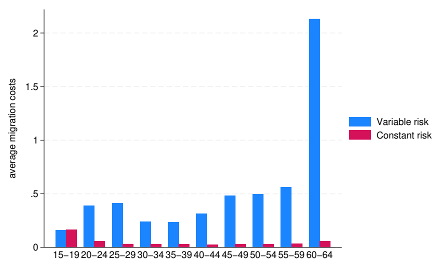
(e) Inter-province Na $\rightarrow$ Na



(c) Intra-province Ag $\rightarrow$ Na

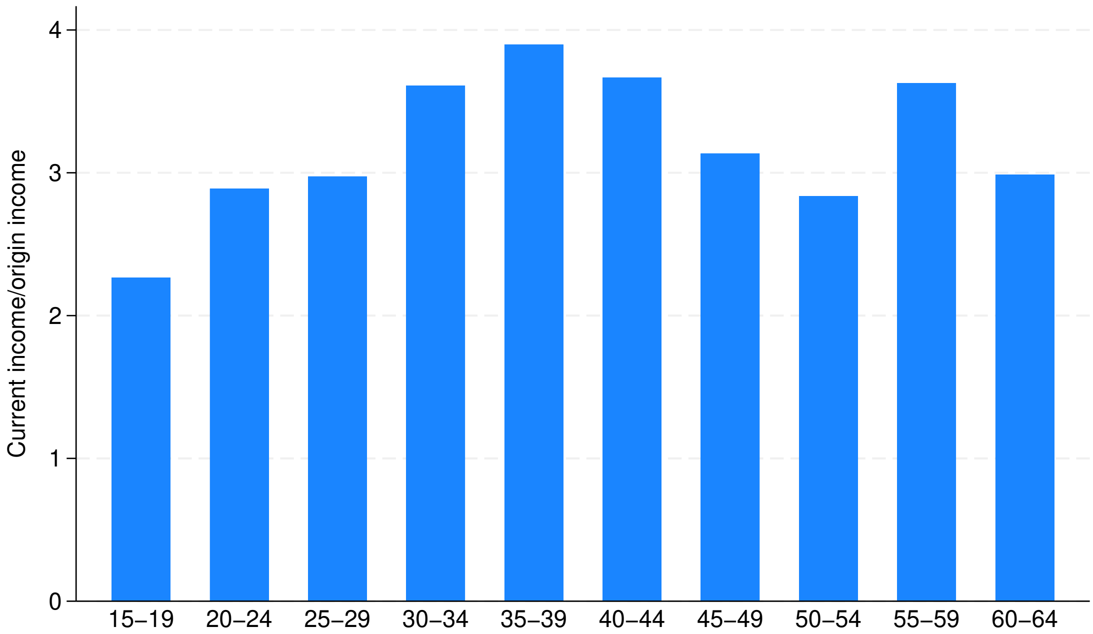


(f) Inta-province Na $\rightarrow$ Ag



Notes: The figures present estimated migration costs across cohorts for different migration paths under two scenarios: (i) under observed risk parameter of each cohort and (ii) assuming all cohorts have the same risk preference parameter ($\rho^a = 0, \forall a$). Panels (a)-(c) present migrations originating from agriculture. Panels (d)-(f) present migrations originating from non-agriculture. Panels (c) and (f) present the costs of switching sectors within a province. Migration costs are measured relative to destination utility.

Figure 7: Estimation of migration costs from survey (CHIP 2007)



Notes: This figure presents estimation of migration costs from CHIP 2007 data. Migration cost is measured as workers current income relative to the income that the worker would have earned if he/she remained at origin location. The graph presents the average of this measure across workers within age groups.

Tables

Table 1: Employment and migration statistics across the 2000, 2005, and 2010 censuses

		2000	2005	2010
	Adults (Age >=26)			
1	Number of adult workers (mil.)	523	562	640
2	Number of adult migrant workers (mil.)	44	49	157
3	Number of adult manufacturing workers (mil.)	61	69	110
	Youth (Age 16-25)			
4	Number of young workers (mil.)	118	117	150
5	Number of young migrant workers (mil.)	28	32	78
6	Number of young manufacturing workers (mil.)	24	28	46
	Shares of adult workers			
	who are migrant (2/1)	8%	9%	24%
	who are in manufacturing (3/1)	12%	12%	17%
	Shares of young workers			
	who are migrant (5/4)	24%	27%	52%
	who are in manufacturing (6/4)	20%	24%	31%

Notes: This table presents employment statistics based on the 2000, 2005, and 2010 (mini)censuses. Migrants in each census include those who arrived in the last five years of the census date. Migration numbers include both within and between prefecture movers.

Table 2: The effect of trade liberalization on sectoral employment shares

	(1) Manufacturing	(2) Secondary	(3) Primary	(4) Tertiary
D*NTRgap	0.173***	0.123***	-0.134**	0.011
	(0.037)	(0.040)	(0.052)	(0.024)
D*I*NTRgap	0.003	0.005	-0.011**	0.006*
	(0.003)	(0.004)	(0.004)	(0.003)
N	19291	19291	19291	19291
R^2	0.884	0.900	0.929	0.865

Notes: Standard errors are clustered at Prefecture level. D_c is a dummy variable which equals 1 for cohorts born in 1986 or later and zero otherwise. I_c is birth year re-centered around 1986. All regressions include prefecture and cohort fixed effects and the following control variables interacted with D_c: export license share, foreign tariff, import tariff, production subsidy, and NTRrate.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: The effect of trade liberalization on sectoral employment shares (no aggregation across census years)

	(1) Manufacturing	(2) Secondary	(3) Primary	(4) Tertiary
D*NTRgap	0.165***	0.103***	-0.094**	-0.009
	(0.034)	(0.035)	(0.047)	(0.023)
D*I*NTRgap	0.004	0.007*	-0.013***	0.006**
	(0.003)	(0.004)	(0.004)	(0.003)
N	66110	66110	66110	66110
R^2	0.810	0.809	0.839	0.711

Notes: Standard errors are clustered at Prefecture level. D_c is a dummy variable which equals 1 for cohorts born in 1986 or later and zero otherwise. I_c is birth year re-centered around 1986. All regressions include prefecture and cohort fixed effects and the following control variables interacted with D_c. All regressions include prefecture, census year and cohort fixed effects, and the following control variables interacted with D_c: export license share, foreign tariff, import tariff, production subsidy, and NTRrate.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: The effect of trade liberalization on migrant share of workers

	(1) Migrant share	(2) Migrant share
D*NTRgap	0.142***	0.139***
	(0.052)	(0.035)
D*I*NTRgap	0.003	0.005
	(0.005)	(0.004)
N	18354	53962
R^2	0.801	0.668

Notes: Standard errors are clustered at Prefecture level. Column (1) is based on data from multiple census years aggregated by cohort-prefecture level. Column (2) is is based on cohort-prefecture-census year variation. Column (1) includes cohort and prefecture fixed effects. Column (2) includes cohort, prefecture and census-year fixed effects. D_c is a dummy variable which equals 1 for cohorts born in 1986 or later and zero otherwise. I_c is birth year re-centered around 1986. All regressions include prefecture and cohort fixed effects and the following control variables interacted with $_c$. All regressions include the following control variables interacted with D_c: export license share, foreign tariff, import tariff, production subsidy, and NTRrate.

$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: Income and income risk elasticity of migration by age groups

	Model-1	Model-2
Diff mean income	3.889***	3.536***
	(0.435)	(0.301)
Diff var income	-2.788***	-2.416***
	(0.333)	(0.230)
Age 15-19 * Diff var income	4.905***	3.943***
	(0.539)	(0.397)
Age 20-24 * Diff var income	2.067***	1.894***
	(0.159)	(0.129)
Age 25-29 * Diff var income	2.101***	1.912***
	(0.186)	(0.143)
Age 30-34 * Diff var income	2.360***	2.161***
	(0.186)	(0.143)
Age 35-39 * Diff var income	2.362***	2.106***
	(0.189)	(0.145)
Age 40-44 * Diff var income	2.194***	2.002***
	(0.185)	(0.145)
Age 45-49 * Diff var income	1.971***	1.754***
	(0.193)	(0.149)
Age 50-54 * Diff var income	1.525***	1.356***
	(0.175)	(0.137)
Age 55-59 * Diff var income	1.590***	1.374***
	(0.200)	(0.151)
Distance	-1.236***	
	(0.010)	
Origin-sector FE	Yes	Yes
Origin-destination FE	Yes	No
Age group FE	Yes	Yes
N	37766	37766
R-square	-0.26	-0.87
First-stage F-stat	11.42	20.44

Notes: This table presents estimation results for migration flow equation. *Diff mean income* is the difference in average income between destination province/sector and origin province/sector. *Diff var income* represents differences in variance of income between destination province/sector and origin province/sector. Column (1) includes origin-destination fixed effects while Column (2) replaces these fixed effects by log of bilateral distance. 60-64 age group are base group.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: Parameters from the main migration model

Parameter	Estimated value	Bootstrap s.e.
	Panel A: Main result	
ρ_{15-19}	-0.089	0.206
ρ_{20-24}	1.371	0.067
ρ_{25-29}	1.353	0.049
ρ_{30-34}	1.220	0.068
ρ_{35-39}	1.219	0.061
ρ_{40-44}	1.305	0.056
ρ_{45-49}	1.420	0.035
ρ_{50-54}	1.650	0.030
ρ_{55-59}	1.616	0.021
ρ_{60-64}	2.434	0.073
κ	3.889	0.434
	Panel B: Robustness	
ρ_{15-19}	0.136	0.190
ρ_{20-24}	1.295	0.064
ρ_{25-29}	1.285	0.044
ρ_{30-34}	1.144	0.058
ρ_{35-39}	1.176	0.052
ρ_{40-44}	1.234	0.050
ρ_{45-49}	1.375	0.033
ρ_{50-54}	1.600	0.028
ρ_{55-59}	1.590	0.015
ρ_{60-64}	2.367	0.062
κ	3.536	0.386

Notes: This table presents parameters from the main migration model. Panel A runs the regression with bilateral distance while Panel B replaces distance by bilateral fixed effects. Standard errors are obtained by bootstrapping with 50 replications.

Table 7: Average migration costs by age group and migration path

	Different Provinces					Same Province	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	$A \rightarrow$ NA	NA $\rightarrow A$	$A \rightarrow A$	NA $\rightarrow$ NA	$A \rightarrow$ NA	NA $\rightarrow A$
15-19	2.16	3.34	0.98	4.52	0.85	0.27	0.18
20-24	5.09	6.08	4.11	9.21	2.88	0.49	0.49
25-29	5.21	6.06	4.36	9.07	2.80	0.47	0.44
30-34	4.41	5.28	3.53	8.23	2.31	0.41	0.32
35-39	4.72	5.48	3.96	8.05	2.64	0.39	0.33
40-44	5.47	6.62	4.33	8.86	3.17	0.46	0.37
45-49	6.95	8.63	5.27	10.47	4.24	0.58	0.48
50-54	9.30	11.16	7.44	13.16	6.26	0.75	0.68
55-59	9.15	12.28	6.02	13.62	5.48	0.95	0.60
60-64	27.69	26.03	29.35	26.72	28.52	2.26	4.49
N	16548	8274	8274	7562	9182	277	277

Notes: The table presents average migration costs under different conditions. Column (1) reports average migration costs when origin and destination provinces are different and origin and destination sectors are different. Columns (2)-(5) report average migration costs when origin and destination provinces are different between and within agriculture (A) and non-agriculture (NA) sectors. Columns (6)-(7) report average migration costs between A and NA sectors. In all cases, migration costs are calculated as a ratio to destination (current) utility of workers.

Table 8: Migration costs and distance

	(1)	(2)
	Migration costs	Migration costs
Log Distance	1.371^{***}	0.911^{***}
	(0.095)	(0.049)
Origin Province-Sector FEs	Y	Y
Destination Province-Sector FEs	Y	Y
Cohort FEs	Y	Y
N	16548	18300
R^2	0.423	0.521

Notes: In Column (1), the migration costs are calculated allowing the risk parameter to vary across cohorts. In Column (2), the migration costs are calculated assuming constant risk parameter $\rho^a = 0$ across all cohorts.

Table 9: Median migration costs by age group and migration path

	Different Provinces					Same Province	
	(1) Overall	(2) $A \to$ NA	(3) NA $\to A$	(4) $A \to A$	(5) NA $\to$ NA	(6) $A \to$ NA	(7) NA $\to A$
15-19	1.13	2.35	0.88	3.18	0.71	0.18	0.13
20-24	4.06	3.20	4.13	8.98	3.61	0.49	0.46
25-29	4.28	3.12	4.51	8.81	3.23	0.49	0.43
30-34	3.65	2.62	3.73	7.84	2.84	0.38	0.31
35-39	3.87	3.19	3.98	7.68	3.39	0.40	0.33
40-44	4.46	5.04	4.41	9.14	3.81	0.44	0.37
45-49	5.71	7.54	5.45	9.64	4.67	0.52	0.48
50-54	7.80	10.38	7.53	13.13	7.01	0.74	0.69
55-59	6.71	12.42	6.26	14.17	5.83	0.91	0.61
60-64	18.26	19.26	18.26	19.26	17.22	1.56	2.62
N	16548	8274	8274	7562	9182	277	277

Notes: The table presents median migration costs under different conditions. Column (1) reports median migration costs when origin and destination provinces are different and origin and destination sectors are different. Columns (2)-(5) report median migration costs when origin and destination provinces are different between and within agriculture (A) and non-agriculture (NA) sectors. Columns (6)-(7) reports median migration costs between A and NA sectors. In all cases, migration costs are calculated as a ratio to destination (current) utility of workers.

Table 10: Parameters from the nested migration model

Parameter	Estimated value	Bootstrap s.e.
κ_s	3.448	0.553
κ_r	1.472	0.198
ρ_{15-19}	-0.010	0.237
ρ_{20-24}	1.142	0.125
ρ_{25-29}	1.242	0.083
ρ_{30-34}	1.000	0.117
ρ_{35-39}	1.007	0.115
ρ_{40-44}	1.155	0.087
ρ_{45-49}	1.371	0.062
ρ_{50-54}	1.434	0.070
ρ_{55-59}	1.546	0.047
ρ_{60-64}	2.116	0.126

Notes: This table presents parameters from the nested migration model. Standard errors are obtained by bootstrapping with 50 replications.

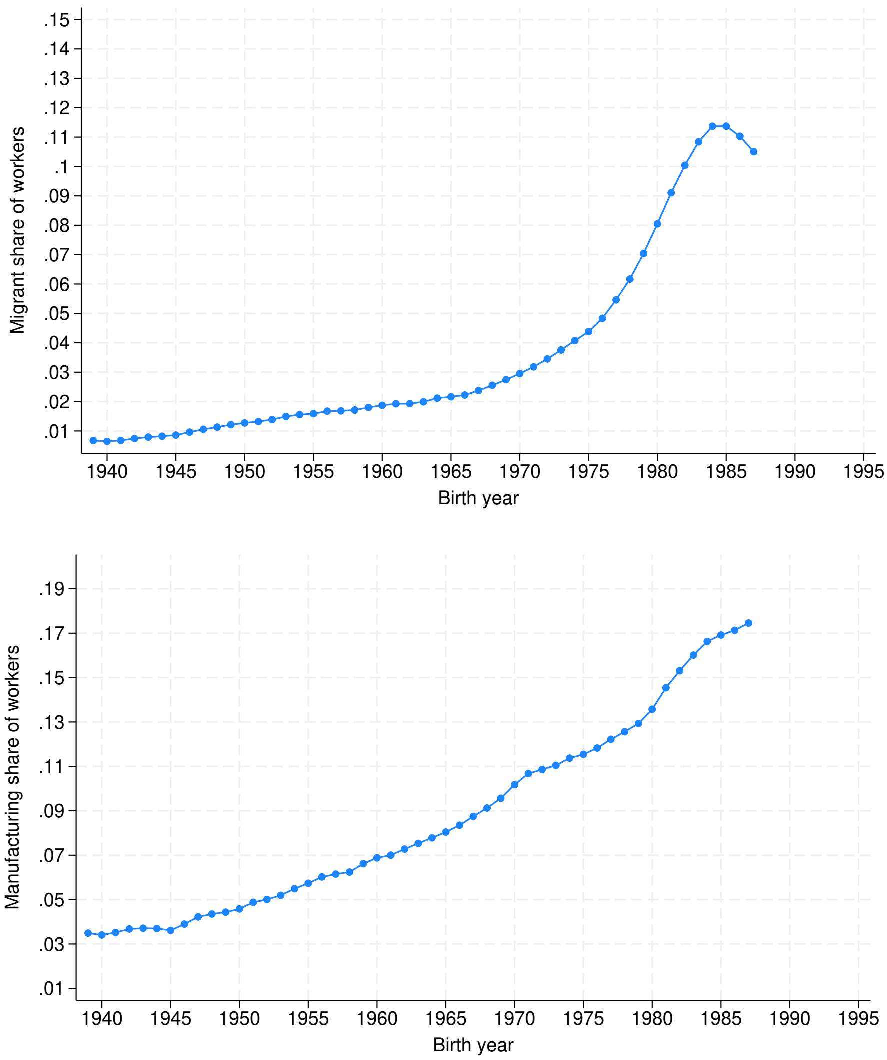
Table 11: Nested migration model: migration costs by age group and migration path

	Different Provinces					Same Province	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	$A \rightarrow$ NA	NA $\rightarrow A$	$A \rightarrow A$	NA $\rightarrow$ NA	$A \rightarrow$ NA	NA $\rightarrow A$
15-19	2.31	3.83	0.79	4.44	0.78	0.26	0.16
20-24	4.68	5.96	3.41	8.90	2.43	0.45	0.39
25-29	5.24	6.21	4.27	9.20	2.79	0.46	0.41
30-34	3.95	5.07	2.83	7.84	1.87	0.37	0.24
35-39	3.94	4.90	2.97	7.25	2.01	0.33	0.24
40-44	5.19	6.49	3.90	8.69	2.87	0.42	0.32
45-49	7.36	9.12	5.60	11.04	4.51	0.59	0.48
50-54	8.03	10.36	5.71	12.07	4.83	0.66	0.50
55-59	9.09	12.33	5.84	13.73	5.29	0.92	0.56
60-64	17.37	20.14	14.61	19.96	14.51	1.74	2.13

Notes: The table presents average migration costs under different conditions. Column (1) reports average migration costs when origin and destination provinces are different and origin and destination sectors are different. Columns (2)-(5) report average migration costs when origin and destination provinces are different between and within agriculture (A) and non-agriculture (NA) sectors. Columns (6)-(7) report average migration costs between A and NA sectors within a province. In all cases, migration costs are calculated as a ratio to destination (current) utility of workers.

Appendix A Migration patterns in Vietnam

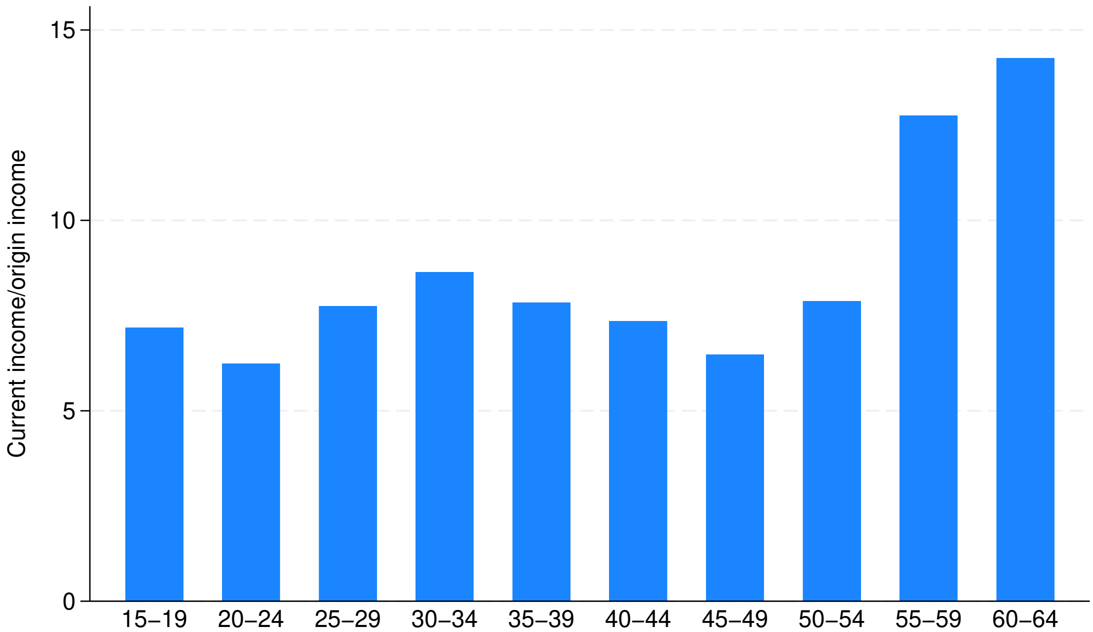
Figure A.1: Migrants and manufacturing share of workers across ages in Vietnam



Notes: This figure presents the share of workers who are migrants and share of manufacturing workers for by birth year. Vietnam had expanded access to the U.S market in 2002. Thus individuals born during 1980s or later are the most exposed to the trade policy shock.

Appendix B Additional results

Figure A.2: Estimation of migration costs from survey (CHIP 2002)



Notes: This figure presents estimation of migration costs from CHIP 2002 data. Migration cost is measured as workers current income relative to the income that the worker would have earned if he/she remained at origin location. The graph presents the average of this measure across workers within age groups.

Table A.1: Income and income risk elasticity of migration by age groups

	Model-1	Model-2
Dest income mean	3.530***	4.579***
	(0.285)	(0.578)
Dest income var	-1.470***	-2.199***
	(0.140)	(0.296)
Age 15-19 * Dest income var	1.773***	3.771***
	(0.257)	(0.504)
Age 20-24 * Dest income var	1.030***	1.158***
	(0.077)	(0.094)
Age 25-29 * Dest income var	0.870***	1.079***
	(0.069)	(0.093)
Age 30-34 * Dest income var	1.295***	1.498***
	(0.078)	(0.106)
Age 35-39 * Dest income var	1.098***	1.447***
	(0.079)	(0.107)
Age 40-44 * Dest income var	0.893***	1.098***
	(0.075)	(0.097)
Age 45-49 * Dest income var	0.506***	0.768***
	(0.071)	(0.099)
Age 50-54 * Dest income var	0.557***	0.755***
	(0.072)	(0.104)
Age 55-59 * Dest income var	0.481***	0.752***
	(0.072)	(0.111)
Distance		-1.246***
Origin-sector FE	Yes	Yes
Origin-destination FE	Yes	No
Age group FE	Yes	Yes
N	36208	36208
R-square	-0.08	0.15
First-stage F-stat	27.19	8.39

Notes: This table presents estimation results for migration flow equation. *Dest income mean* is the average income at destination province/sector. *Dest income var* represents variance of income at destination province/sector. Column (1) includes origin-destination fixed effects while Column (2) replaces these fixed effects by log of bilateral distance. 60-64 age group are base group..
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.2: Implied risk preference parameter by age group ρ^a

Age group	ρ^a (Model-1)	ρ^a (Model-2)
15-19	0.83	0.31
20-24	1.25	1.45
25-29	1.34	1.49
30-34	1.10	1.31
35-39	1.21	1.33
40-44	1.33	1.48
45-49	1.55	1.63
50-54	1.52	1.63
55-59	1.56	1.63
60-64	1.83	1.96

Notes: This table presents risk preference parameters corresponding to the migration flow equation presented in the previous table.

Table A.3: Average migration costs by age group and migration path: Robustness check

	Different Provinces					Same Province	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	$A \rightarrow$ NA	NA $\rightarrow A$	$A \rightarrow A$	NA $\rightarrow$ NA	$A \rightarrow$ NA	NA $\rightarrow A$
15-19	3.07	4.30	1.85	5.82	1.60	0.33	0.37
20-24	4.88	5.95	3.82	9.03	2.68	0.47	0.46
25-29	5.64	6.36	4.91	9.54	3.16	0.49	0.50
30-34	4.19	5.13	3.24	8.00	2.12	0.40	0.29
35-39	5.01	5.74	4.29	8.41	2.86	0.40	0.36
40-44	6.40	7.46	5.34	9.93	3.90	0.51	0.45
45-49	9.18	10.72	7.64	12.94	6.13	0.71	0.69
50-54	8.40	10.45	6.34	12.30	5.33	0.70	0.58
55-59	8.86	12.01	5.72	13.33	5.20	0.92	0.57
60-64	11.26	15.07	7.46	15.43	7.18	1.31	1.01
N	16548	8274	8274	7562	9182	277	277

Notes: The table presents average migration costs under different conditions. Column (1) reports average migration costs when origin and destination provinces are different and origin and destination sectors are different. Columns (2)-(5) report average migration costs when origin and destination provinces are different between and within agriculture (A) and non-agriculture (NA) sectors. Columns (6)-(7) report average migration costs between A and NA sectors. In all cases, migration costs are calculated as a ratio to destination (current) utility of workers.

Table A.4: Average migration costs by age group and migration path (incorporating amenities)

	Different Provinces					Same Province	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	$A \rightarrow$ NA	NA $\rightarrow A$	$A \rightarrow A$	NA $\rightarrow$ NA	$A \rightarrow$ NA	NA $\rightarrow A$
15-19	1.24	1.97	0.51	2.67	0.44	0.21	0.10
20-24	3.21	3.69	2.72	5.54	1.93	0.39	0.39
25-29	3.28	3.67	2.89	5.46	1.89	0.38	0.36
30-34	2.77	3.17	2.36	4.95	1.55	0.33	0.27
35-39	2.87	3.26	2.48	4.77	1.68	0.31	0.26
40-44	3.48	4.07	2.89	5.45	2.13	0.37	0.31
45-49	4.26	5.19	3.34	6.33	2.70	0.46	0.38
50-54	5.76	6.69	4.83	7.99	4.08	0.59	0.55
55-59	5.55	7.25	3.84	8.04	3.51	0.71	0.48
60-64	19.47	16.50	22.45	16.94	21.86	1.82	4.16
N	16548	8274	8274	7562	9182	277	277

Notes: The table presents average migration costs under different conditions. Column (1) reports average migration costs when origin and destination provinces are different and origin and destination sectors are different. Columns (2)-(5) report average migration costs when origin and destination provinces are different between and within agriculture (A) and non-agriculture (NA) sectors. Columns (6)-(7) reports average migration costs between A and NA sectors. In all cases, migration costs are calculated as a ratio to destination (current) utility of workers.

Appendix C Description of the Iterative Procedure

To estimate the parameters of the nested migration model, we employ an iterative estimation procedure. This method is necessary because the relative attractiveness (Γ), which captures relative attractiveness of province-sector, is itself a function of the elasticities we aim to identify.

1. Initialization: The procedure begins with initial values for the sectoral elasticity (κ_s), regional elasticity (κ_r), cohort-specific risk aversion (ρ^a), and $\tilde{\gamma}^{kl}$.
2. Looping for Consistency: In each iteration, the model performs the following sequence:
   - Relative Attractiveness (Inclusive Value Construction): We calculate $\Gamma_j^{a,k}$ and $\Gamma_i^{a,k}$ using the current iteration's parameters.
   - Linear IV Regression: We estimate the migration equation using Instrumental Variables (IVs) to address the endogeneity of the mean income differences and variance income differences between destination and origin. The relative attractiveness $\left(\ln \Gamma_j^{a,k} - \ln \Gamma_i^{a,k}\right)$ enters as a standard regressor.
   - Parameter Updating: We update κ_s, κ_r, and ρ^a from the regression coefficients. We update the switching costs ($\tilde{\gamma}^{kl}$) by extracting the origin-sector to destination-sector fixed effects. These updated frictions are then fed back into the inclusive value construction for the next iteration.
3. Convergence: The loop continues until the changes in κ_s and κ_r fall below a threshold of 10^{-2}.

Appendix D Derivation of Taylor expansion

Here we provide detailed derivation of the Taylor expansion of the net benefit equation.

Let the utility of a deterministic wage at origin be $u(w_o)$. If an agent chooses to stay at origin (o) from age a until T, their lifetime value function is deterministic:

$$V_{stay}(a) = \sum_{t=a}^{T} u(w_o) = (T - a + 1)u(w_o)$$

If the agent chooses to migrate to the destination (d) at age a, they pay a one-time upfront migration cost C (scaled in utility units for simplicity) and earn the stochastic wage $\tilde{w}_d = w_d + \epsilon_{dt}$ for the remaining periods:

$$V_{migrate}(a) = \sum_{t=a}^{T} \mathbb{E}[u(w_d + \epsilon_{dt})] - C = (T - a + 1)\mathbb{E}[u(w_d + \epsilon_{dt})] - C$$

The exact Net Benefit (NB) of migrating at age a is:

$$NB(a) = V_{migrate}(a) - V_{stay}(a) = (T - a + 1)\Big(\mathbb{E}[u(w_d + \epsilon_{dt})] - u(w_o)\Big) - C$$

To capture how risk impacts the decision, we approximate the expected utility term $\mathbb{E}[u(w_d + \epsilon_{dt})]$ using a second-order Taylor series expansion around the expected destination wage w_d:

$$u(w_d + \epsilon_{dt}) \approx u(w_d) + u'(w_d)\epsilon_{dt} + \frac{1}{2}u''(w_d)\epsilon_{dt}^2$$

Taking the expectation of both sides:

$$\mathbb{E}[u(w_d + \epsilon_{dt})] \approx \mathbb{E}[u(w_d)] + u'(w_d)\mathbb{E}[\epsilon_{dt}] + \frac{1}{2}u''(w_d)\mathbb{E}[\epsilon_{dt}^2]$$

Since $\mathbb{E}[\epsilon_{dt}] = 0$ and $\mathbb{E}[\epsilon_{dt}^2] = \sigma_d^2$ (the variance of destination income), this simplifies to:

$$\mathbb{E}[u(w_d + \epsilon_{dt})] \approx u(w_d) + \frac{1}{2}u''(w_d)\sigma_d^2$$

Next, we expand the utility of the expected destination wage $u(w_d)$ around the home wage w_o using a first-order Taylor expansion to represent the utility premium in terms of wage differences:

$$u(w_d) \approx u(w_o) + u'(w_o)(w_d - w_o)$$

Substitute this back into our expected utility equation above:

$$\mathbb{E}[u(w_d + \epsilon_{dt})] \approx u(w_o) + u'(w_o)(w_d - w_o) + \frac{1}{2}u''(w_d)\sigma_d^2$$

Now, substitute the approximated expected utility back into the Net Benefit equation:

$$NB(a) \approx (T - a + 1)\left[u(w_o) + u'(w_o)(w_d - w_o) + \frac{1}{2}u''(w_d)\sigma_d^2 - u(w_o)\right] - C$$

The $u(w_o)$ terms cancel out, giving:

$$NB(a) \approx (T - a + 1)\left[u'(w_o)(w_d - w_o) + \frac{1}{2}u''(w_d)\sigma_d^2\right] - C$$

Divide the entire equation by marginal utility $u'(w_d)$ and define risk-aversion parameters as $\gamma = -\frac{u''(w_d)}{u'(w_o)}$ (assuming evaluating marginal utilities across the baseline wages is close to a constant local risk aversion factor). For large horizons $(T-a+1) \approx (T-a)$, and we get:

$$NB(a) \approx (T - a)(w_d - w_o) - \frac{1}{2}\gamma(T - a)\sigma_d^2 - C$$

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