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# Slowdown in Immigration, Labor Shortages, and Declining Skill Premia

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**Abstract:** We document a slowdown in low-skilled immigration that began around the onset of the Great Recession in 2007, which was associated with a subsequent rise in low-skilled wages, a decline in the skill premium, and labor shortages in service occupations. Falling returns to education also coincided with a decline in the educational attainment of native workers. We then develop and estimate a stochastic growth model with endogenous immigration and training to rationalize these facts. Lower immigration leads to higher wages for low-skilled workers but also to higher consumer prices and lower aggregate consumption. Importantly, the decline in the skill premium reduces the incentive to train native workers and hurts aggregate productivity over time, which reduces welfare. We assess the implications of stimulus policies implemented during the COVID-19 pandemic and show that the shortage of low-skilled immigrant labor amplified the increase in consumer prices, partially eroding the effectiveness of stimulus.

JEL classification: F16, F22, F41

Key words: international labor migration, skill premium, task upgrading, heterogeneous workers

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# 1 Introduction

We document the protracted slowdown in low-skill immigration since the Great recession in 2007 and study its impact on labor market dynamics, macroeconomic performance and welfare. We first use regional U.S. Census data to establish new empirical facts related to the fall in low-skill immigration and the ensuing changes in labor markets dynamics since the Great Recession. We then use these findings to motivate a novel stochastic growth model that features endogenous immigration, training and offshoring choices. We estimate the model to address the following questions: What were the consequences of the slowdown in low-skill immigration for employment and wages by different skill levels, for the skill premium, and for the native workers' decision to train and invest in education? What were the implications of those changes for macroeconomic performance and welfare?

**Motivation and evidence from the employment data.** Immigration is central for understanding the labor market dynamics and living standards in the United States. According to U.S. Census Bureau data, between 1980 and 2007, the foreign-born prime-age population (25-54 years old) increased by 16.3 million people, averaging an annual growth rate of 4.8 percent and accounting for 29 percent of the increase in the total prime-age U.S. population. However, the inflow of immigrants has steeply declined since the Great Recession in 2007, and the average annual growth rate of foreign-born population more than halved to 1.9 percent for this age group, while the total population remained roughly unchanged at around 126 million between 2007 and 2019. This reduction in foreign-born population has important consequences for countries with aging populations like the U.S. We estimate that, if the foreign-born population had continued to grow at the average rate from before the Great Recession, the total prime-age U.S. population would have been 11 percent higher in 2019.[1] These numbers are striking, yet they represent lower-bound estimates of the impact of the immigration slowdown for U.S. population growth, since they likely understate the contribution of undocumented immigration, which is largely low-skill. By conservative estimates, undocumented immigration increased from negligible numbers in the early 1980s to about 12.2 million in 2007, but has declined to 10.5 million during the following decade.[2]

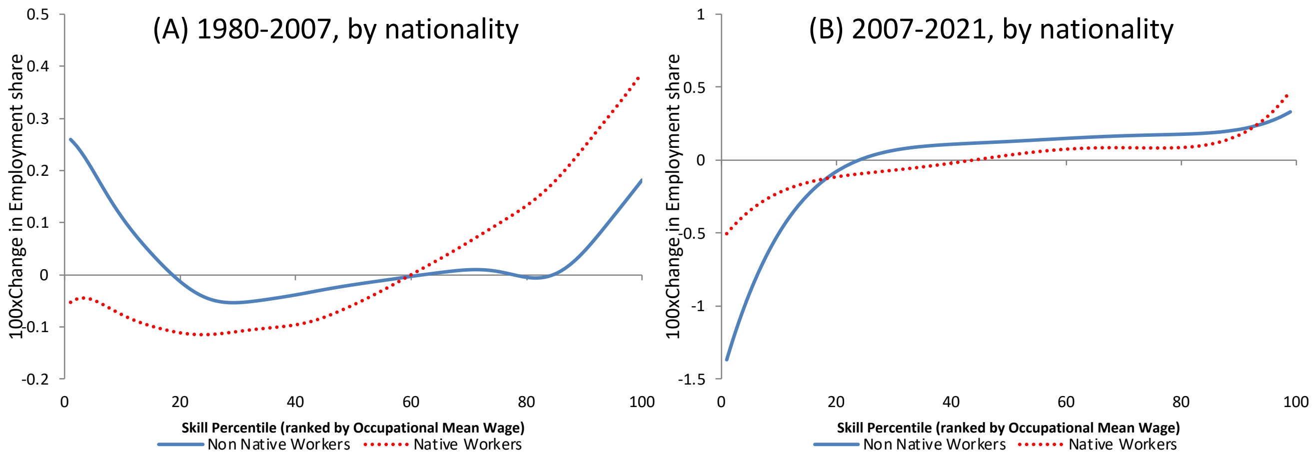
To contextualize our analysis, we first document marked differences in the evolution of native and non-native employment across the skill distribution in two distinct periods. Figure 1(A) shows employment growth across occupations grouped into percentiles and ranked by skill (x-axes) between 1980 and 2007 like in Autor and Dorn (2013), which we break down by native (dotted line) and foreign-born workers (solid line). For natives, net employment growth was mostly concentrated in high-skill occupations, with negative growth in low-skill occupations. For foreigners, instead, the bulk of employment growth was at the bottom quartile of the skill distribution. Figure 1(B) shows the striking reversal of these employment dynamics in the post-2007 period that produced negative employment growth especially for foreign-born workers at the bottom quartile of the skill distribution, reflecting the decline in low-skill immigration.

[1] We compute these figures from U.S. Census Bureau data, Current Population Survey, Annual Social and Economic Supplement.

[2] Krogstad et al. (2019) documents that 71 percent of undocumented immigrants are in the prime age group, compared to 38 percent for the total U.S. population. If we consider that most 16-24 year old undocumented immigrants also work, since they cannot pursue tertiary education in the U.S., around 85 percent of these immigrants are of working age.

Employment in the bottom quartile of the skill distribution is concentrated in service occupations (such as child care, restaurant and hotel workers, domestic and office cleaners, gardeners, health aides, etc.) and construction laborers. See the Appendix for details. Important to our analysis, these occupations require the execution of jobs in the same geographic location where the final consumption takes place, hence cannot be offshored overseas, making the hiring of immigrant workers the only viable alternative if consumer demand increases.

**Figure 1:** Smoothed changes in the growth of employment by skill percentile and nationality




*Note:* We use U.S. Census/American Community Survey (ACS) data to compute changes in employment shares between 1980 and 2007 (left panel) and 2007-2021 (right panel). The occupations are sorted into 100 percentiles based on the mean occupational wages in the starting periods as a proxy for skill. The change in shares is obtained as the difference between the share of total U.S. employment in the starting and ending periods for each percentile. The smooth changes are obtained with a locally weighted polynomial regression between the change in employment shares and the corresponding percentiles.

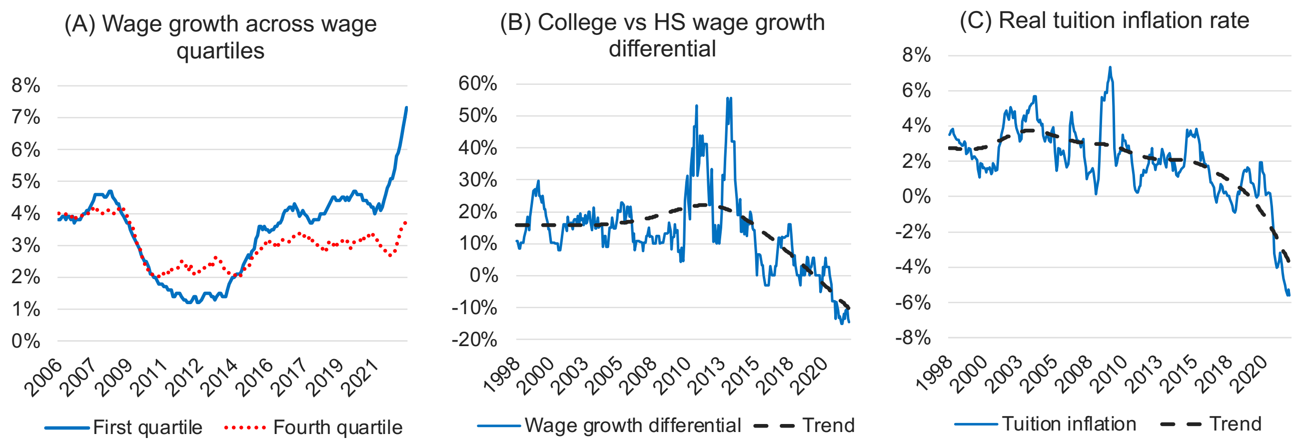
The relative shortage of low-skill immigrant labor contributed to the rapid growth of low-skill wages over the past decade. Figure 2(A) shows the nominal wage growth for jobs in the first quartile (red-dashed line) versus the fourth quartile (blue-solid line) of the earnings distribution. The faster wage growth for low-skill jobs coincided with a sharp decline in the college skill premium, shown in Figure 2(B). The unprecedented fall in the skill premium reverses a four-decade upward trend.[3] Interestingly, the decline in the skill premium coincided with a decline in the inflation-adjusted cost for tuition, as shown in Figure 2(C), consistent with the lower return from investing in education over the period.

**Evidence from regional data and the design of the theoretical model.** We complement our novel aggregate-level evidence with four new facts based on regional data from the U.S. Census' American Community Survey—which provides the characteristics of workers residing in different states, metropolitan areas and commuting zones—to shed new light on the role of low-skill immigration in shaping U.S. labor market dynamics. In turn, these facts are used to develop a theoretical model with realistic dynamics for immigration.

Fact I shows that the positive correlation between the skill premium and low-skill immigration is robust across states, metropolitan areas and commuting zones. Consistently, in our structural model,

[3] See for instance Krusell et al. (2000) and Acemoglu and Autor (2011) among many others

**Figure 2:** Wage growth across wage quartiles, college vs high school wage growth differential, and real tuition inflation




*Note:* Panel (A) illustrates the monthly year-on-year nominal wage growth for the first (red-dotted curve) and fourth (blue-solid curve) quartiles in the earnings distribution. Panel (B) illustrates the monthly year-on-year wage growth percentage differential between workers with college and high school (or less). Panel (C) illustrates the monthly year-on-year percentage change in tuition costs (tuition, other school fees, and childcare) deflated by the CPI index. The dashed curves in Panels (B) and (C) are the trend estimated with an HP filter with a smoothing parameter of 100,000.

the arrival of low-skill immigrant workers from the South boosts labor supply and lowers low-skill wages in the destination economy (Home). Fact II shows that low-skill immigration across commuting zones is positively correlated with the initial low-skill wage at the destination, motivating that in the model, the migration decision of Southern workers is endogenous, and the key factor behind it is the expected wage in the non-tradable sector at the destination. Fact III shows that a more restrictive enforcement of immigration policies at the state level is associated with a lower inflow of unauthorized immigrants, motivating the presence of sunk migration costs in the model to capture the restrictiveness of immigration policy. Fact IV shows that educational attainment is positively correlated with the skill premium, justifying the key role of skill premia in the model driving the endogenous training decision of households.

Our model economy consists of two large regions (Home and Foreign) that trade with each other and a third small region (South) that is the origin of low-skill immigrants, who in turn work in the (non-tradable) service sector in the Home region. We incorporate elements in the model that build on earlier empirical and theoretical advances from the literature. Like in Grossman and Rossi-Hansberg (2008), labor *tasks* rather than *goods* are traded endogenously between Home and Foreign countries, to which we refer as "offshoring" like in Mandelman and Zlate (2022). Due to remarkable declines in transportation and communication costs, international trade now increasingly consists on breaking down the production process of final goods into separate labor tasks that can be executed at different locations. We model this phenomenon with fixed and iceberg costs of task offshoring, as well as a stochastic shock to the iceberg cost that we estimate with data. Following this approach, our model is able to disentangle the separate contributions of offshoring (international trade) and low-skill immigration to the skill premium dynamics. In turn, these developments determine endogenously the choice of skill acquisition (i.e., training) subject to time-varying tuition costs.

**Immigration, macroeconomic performance and welfare.** We estimate our model with the Bayesian method that uses the full information from the complete set of equations in the estimation of parameters and provides estimates of the latent variables. We show that the estimated model fits the data closely across several dimensions. In particular, we find that the flows of low-skill immigrants and time-varying offshoring costs predicted by our model as latent variables are close to their empirical counterparts, which are proxied by the number of individuals apprehended by U.S. patrol officers at the U.S./Mexico border, and a trade-weighted measure of bilateral trade costs we construct from the ESCAP-World Bank bilateral database–which is a comprehensive measure that goes beyond transportation costs.[4]

Our estimated model establishes three important results on the impact of low-skill immigration for the labor market dynamics, macroeconomic performance, and welfare. First, the recent decline in the skill premium is largely accounted by the slowdown in low-skill immigration since 2007. In contrast, offshoring did not play a sizeable role in shaping the U.S. skill premium. Furthermore, the slowdown in low-skill immigration was largely driven by more restrictive immigration policy, and the decline in skill premia discouraged training by the native workers.

Second, it took time for the decline in low-skill immigration after the Great Recession in 2007 to generate effective labor market shortages. The Great Recession, the acute slowdown in housing construction, and the slow recovery of employment subsequently created sizable slack in labor markets. The effect of successive years of slow low-skill immigration only became visible when the labor market tightened in the years preceding the onset of the COVID-19 pandemic.[5]

Third, changes in migration policy have critical implications for welfare. The increasing restrictiveness of U.S. immigration policy and the associated decline in low-skill immigration since the mid-2000s lowered welfare from the representative U.S. household.[6] Although declining low-skill immigration boosts wages for low-skill native workers, it also leads to more expensive non-tradable services that diminish the household's purchasing power. More important for our quantitative analysis, the lower skill premium discourages investment in skill acquisition by native workers, which ultimately hinders labor productivity and reduces total income and welfare.

**The CARES Act in March 2020.** We apply the estimated model to study the impact of labor shortages during the COVID-19 pandemic. We model the rapid surge in consumer demand associated with several rounds of policy stimulus payments initiated with the Coronavirus Aid, Relief, and Economic Security (CARES) Act in March 2020 and show that the welfare gains from policy stimulus were substantially hindered by the shortage of low-skill immigrant workers in non-tradable occupations whose output cannot be offshored. The acute shortages led to a spike in low-skill wages in response to the stimulus package, which increased consumer prices and eroded the efficacy of the policy stimulus.

[4] Not only transport costs and tariffs are computed, but also language/communication barriers among others. Data is available at: https://www.unescap.org/resources/escap-world-bank-trade-cost-database

[5] Consistently, the unemployment to vacancies ratio peaked at 6.9 in 2009 and declined very slowly to reach 1.1 in 2016 (U.S. Bureau of Labor Statistics)

[6] Several restrictive immigration policies were enacted over the period. Major legislation approved by Congress includes: the Homeland Security Act of 2002, Enhanced Border Security and Visa Entry Reform Act of 2002, REAL ID Act of 2005, Secure Fence Act of 2006, and the Jaime Zapata Border Enforcement Security Task Force Act of 2012.

**Related Literature.** To the best of our knowledge, we are the first to: (a) study the empirical link between the fall in low-skill immigration, labor shortages, the unprecedented decline in the skill premium, and the associated impact on training choices of natives; (b) assess its welfare implications through the lens of a structural model which accounts for this novel micro evidence . Our general result that immigration plays an important role in driving the employment and wage dynamics in the U.S. labor market is consistent with several studies. Ottaviano and Peri (2012), Borjas et al. (2008), and Friedberg and Hunt (1995) document a negative impact of migration on low-skill native employment and wages. Cortés (2008) finds that the inflow of immigrants into the United States lowers the price of services provided by low-skill workers. In turn, Autor and Dorn (2013) focus their analysis on employment at the left tail of the skill distribution, showing that employment growth in low-skill occupations through mid-2000s was accounted by the emergence of (non-tradable) service occupations. Burstein et al. (2020) highlight that labor market adjustment to immigration differs across tradable and non-tradable occupations. Hunt (2017) and Jackson (2015) show empirically that a higher prevalence of low-skill immigration is associated with higher educational attainment among natives.[7]

Our modelling of offshoring is based on the framework with *trade in tasks* developed by Grossman and Rossi-Hansberg (2008), which we expand to include a continuum of tasks executed by heterogeneous workers in a dynamic general equilibrium setting as in Mandelman (2016).[8] Mandelman and Zlate (2022) assess the role of automation and offshoring using a model of trade in tasks. Unlike us, they focus on the patter of labor market polarization before the Great Recession, which precedes the severe labor shortages that are the main focus of our analysis.[9]

We are also related to Ottaviano et al. (2013), Caliendo et al. (2021) and Mehra and Kim (2023) who study immigration, trade and offshoring. Monràs (2020) identifies migration shocks driving low-skill wage dynamics using the Mexican Peso crisis. Finally, Burstein and Vogel (2017) and Cravino and Sotelo (2019) studies the effect of international trade on the skill premium, and Autor et al. (2013, 2016) study the adjustments in the U.S. labor market to the emergence of China as a key player in world trade.

The remainder of the paper is organized as follows. Section 2 presents the new facts based on regional data. Section 3 develops the model. Section 4 presents the results from the estimation of the model. Section 5 evaluates the fit of the model and it studies the propagation of various shocks to the economy, interpreting historical episodes within the period 1983-2018. Section 6 studies the welfare implications. Section 7 concludes.

[7]In addition, Di Giovanni et al. (2015), Kennan (2013), Klein and Ventura (2009), Mandelman and Zlate (2012), Bound et al. (2017) and Piyapromdee (2021) develop general equilibrium models of international labor migration, finding welfare gains from lower immigration barriers. Monràs et al. (2020) studies the aggregate effects of providing a legal status to undocumented immigrants.

[8]The modeling of worker heterogeneity across skills resembles the framework with firm heterogeneity across productivity levels proposed in Ghironi and Melitz (2005), which is also used to model offshoring through vertical FDI in Zlate (2016).

[9]Other important differences from the aforementioned study are the following. First, the previous paper uses a two country model in which labor immigration was exogenous. In our new model, migration decisions are derived from the optimization problem of households in a third country (South) in response to changes to immigration policy and wage differentials. Second, the model in the previous paper was deterministic in nature and only allowed for the analysis of long-run transition dynamics. In contrast, the stochastic growth model in our paper allows to explore short-run dynamics following transitory shocks, which are needed to identify structural parameters driving the recent reversal in the skill premium. Third, our new study features endogenous training in the presence of a time-varying sunk cost, which is estimated with real tuition costs data. Fourth, our paper provides a welfare analyses that is absent in the previous work.

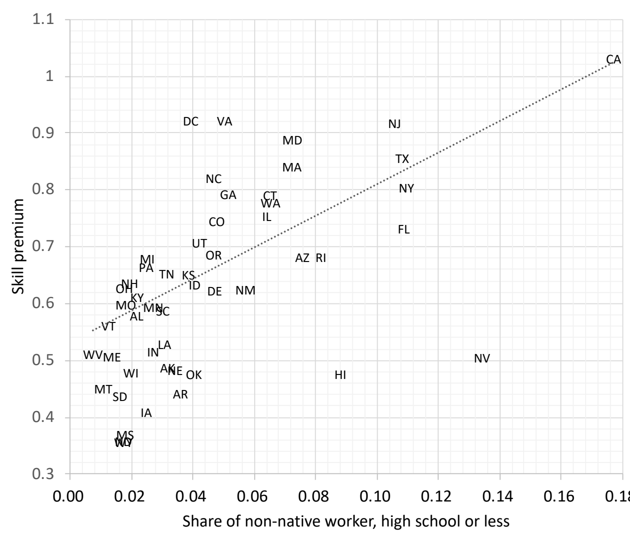
# 2 Regional Evidence

In this section, we provide new empirical evidence based on regional data on how low-skill immigration shapes the U.S. labor market, which motivates important elements in the structure of our theoretical model in Section 3. We use the American Community Survey (ACS) data, annually administered by the U.S. Census Bureau, and involving over 3.5 million households (i.e., approximately five percent of the total population) since 1996. The ACS is the largest running survey of households in the U.S. and it provides individual information—such as place of birth, age, wage income, education, and occupation—of households across the country. We establish four empirical facts at three alternative concepts of regions: state, metropolitan area, and commuting zone.[10]

## 2.1 Fact I: The Skill Premium is Positively Correlated with Low-skill Immigration

We measure region $i$'s skill premium in year $t$ as $sp_{i,t} = w_{i,t}^{C}/w_{i,t}^{HS} - 1$, where $w_{i,t}^{C}$ and $w_{i,t}^{HS}$ are the average hourly wage for working-age full-time workers with college and high school or less, respectively. We measure low-skill immigrant density, $im_{i,t}$, as the share of foreign-born low-skill (high school or less) population among the working-age population.

**Figure 3:** Skill premium is positively correlated with low-skill immigration




*Note:* This figure shows the scatter plot between skill premium and low-skill immigrant density in 2021 across states. Skill premium is the percentage hourly wage differential between college graduates and high school or less for working-age full-time workers in the U.S. Low-skill immigrant density is the share of non-native low-skill (high school or less) population among the working-age population.

Figure 3 displays the scatter plot between skill premium ($sp_{i,t}$, y-axes) and the density of low-skill immigrant ($im_{i,t}$, x-axes) across the U.S. states in 2021, the ending year of our sample. States with a high density of low-skill immigrant, such as California and New Jersey, are associated with a high skill

[10]The metropolitan area is a conventional definition of a region in the literature on immigration (Card, 2009). Furthermore, commuting zone is a better-defined labor market than the previous two concepts because workers can easily commute within them, as shown in Autor et al. (2013).

premium. More rigorously, we estimate the following cross-sectional regression using data in 2021 for three different definitions of region, respectively: $sp_{i,2021} = \alpha + \beta im_{i,2021} + \epsilon_i$, where $sp_{i,2021}$ and $im_{i,2021}$ are the skill premium and the low-skill immigrant intensity in 2021. Columns (1), (3), and (5) of Table 1 show the estimation results at the state, metropolitan areas, and commuting zones levels, respectively. Consistent with our hypothesis, low-skill immigration is positively correlated with skill premia, and the estimates are statistically significant. For example, the point estimates shown in Column (1) indicate that a state's skill premium would be 3.36 percentage points higher in a state with one percentage higher intensity of immigration.

As pointed out in Card (2009), however, skill premium and immigration are both affected by demand factors that are missing in our regression, making the OLS estimates potentially biased. Intuitively, higher demand for low-skill workers would increase low-skill immigration and decrease the skill premia. Hence, we follow Card (2009) by constructing the instrumental variable, $\widehat{im}_{i,2021}$, based on the historical distribution of immigrants from the same source country across regions. The intuition for the instrumental variable is that immigrants tend to settle in country-specific enclaves. For example, Mexican immigrants tend to cluster in Los Angeles and Chicago. This clustering entails a predetermined distribution of immigrants across regions that is uncorrelated with regional labor demand shock. Specifically, we define the instrument as:

$$\widehat{im}_{i,2021} = \sum_k \lambda^k_{i,2005} \text{Inflow}^k_{2010-2021},$$

where $k$ indicates the source country of immigrants. The parameter $\lambda^k_{i,2005}$ is the fraction of low-skill immigrants from source country $k$ who lived in region $i$ in 2005. The variable $\text{Inflow}^k_{2010-2021}$ is the inflow of low-skill immigrants from the source country $k$ to *all* the United States between 2010 and 2021. A natural prediction of the change in the number of low-skill immigrants from source country $k$ between 2010 and 2021 in ragion $i$ is $\lambda^k_{i,2005}$ multiplied by $\text{Inflow}^k_{2010-2021}$. The key idea of the instrumental variable is that neither $\text{Inflow}^k_{2010-2021}$ or $\lambda^k_{i,2005}$ are endogenously determined by changes in labor demand specific to any of the regions between 2010 and 2021.

Columns (2), (4), and (6) of Table 1 show the GMM estimates resulting from our instrumental variable. Similar to our OLS estimation, we find that low-skill immigration is positively correlated with the skill premium. The GMM estimates are larger than the OLS estimates, corroborating our initial evidence. As discussed above, this results from the negative correlation between skill premia and low-skill immigration induced by demand factors alone.

## 2.2 Fact II: Low-skill Immigration Positively Correlates with Initial Low-skill Wages

We next show that low-skill immigration is positively correlated with the initial level of low-skill wages. Suppose a region is hit by a positive shock to low-skill labor demand, which would increase low-skill wages and attract more immigrants of this skill group to live in the region. It is difficult to pin down these demand innovations with our reduced-form analysis. To address this identification issue, we resort to Autor et al. (2013), who show that the rapid surge in imports from China had an outsize impact on import-competing industries that were disproportionately located across the country. The regions

**Table 1:** The skill premium is positively correlated with low-skill immigration

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Definition of region | State | | Metropolitan area | | Commuting zone | |
| Estimation method | OLS | GMM | OLS | GMM | OLS | GMM |
| Low-skill immigrant density | 3.36*** | 4.05*** | 1.26*** | 3.26*** | 1.72*** | 2.27*** |
| | (0.62) | (1.67) | (0.26) | (0.61) | (0.17) | (0.54) |
| Constant | 0.47*** | 0.43*** | 0.55*** | 0.43*** | 0.36*** | 0.34*** |
| | (0.04) | (0.08) | (0.02) | (0.03) | (0.01) | (0.02) |
| Adj R-squared | 0.36 | - | 0.08 | - | 0.12 | - |
| Observations | 51 | 51 | 260 | 260 | 741 | 741 |

*Note:* The dependent variable is the skill premium in 2021. The independent variable is the low-skill immigrant density in 2021. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

most affected by the China's trade shock, therefore, resulted in heterogeneous labor market outcomes for workers of different skill across regions. We thus use the exogenous change in the regional exposure to the China's trade shock between 2000 and 2007, as an instrumental variable in estimating the following cross-sectional regression: $\text{Inflow}_{i,2010-2021} = \alpha + \beta ln\left(w^{HS}_{i,2010}\right) + \epsilon_i$, where $\text{Inflow}_{i,2010-2021}$ is the inflow rate of low-skill immigrants into commuting zone $i$ between 2010 and 2021.[11] The variable $w^{HS}_{i,2010}$ is the low-skill wage of commuting zone $i$ in 2010, which is correlated with our instrumental variable given the persistent effect of trade shocks (Autor et al., 2016). Table 2 shows the estimation results. Namely, a higher low-skill wage is associated with larger inflows of low-skill immigrants.

**Table 2:** Low-skill immigration inflow is positively correlated with low-skill wage

| Definition of region | Commuting zone |
|---|---|
| Estimation method | GMM |
| Low-skill wage | 0.12*** |
| | (0.04) |
| Constant | -0.31*** |
| | (0.09) |
| Observations | 660 |

*Note:* The dependent variables are the inflow rate of low-skill immigrants between 2010 and 2021. The independent variable is the log low-skill wage in 2010. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

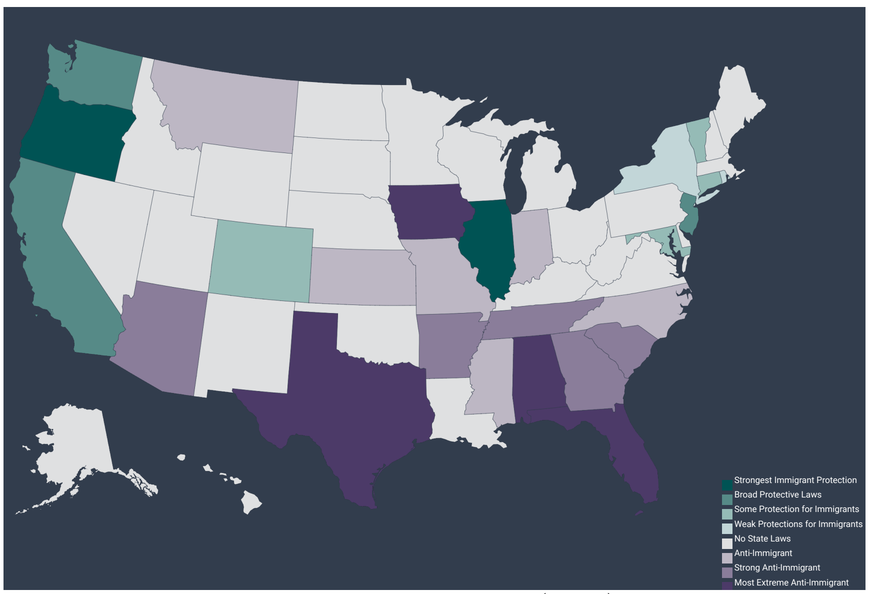
### 2.3 Fact III: Immigration Policy Enforcement Restrains Low-skill Immigration

As we will show in Section 4, the U.S. federal government has significantly intensified immigration enforcement from 2007 onward. In practice, however, the response was different across state legislatures and governors with different political affiliations. The Immigrant Legal Resource Center (ILRC) measures how single states contribute to immigration enforcement from the study of the recent state and local law and legislation. ILRC constructs immigration enforcement measures that fall into four general categories: information and resource sharing with Immigration and Customs Enforcement (ICE, thereafter), jail-to-ICE transfers, patrol officer collusion with ICE, and contracts with ICE or the U.S. Customs and

[11]Specifically, $\text{Inflow}_{i,2010-2021}$ is the ratio of the number of inflow of low-skill immigrants into commuting zone $i$ between 2010 and 2021 to the commuting zone's population in 2021. We focus on commuting zone since the instrumental variable data is unavailable for state and metropolitan areas.

Border Protection agency. Those separate measures are aggregated in a composite index ranging between one and five, with a higher score indicating a more protective immigration policy. Figure 4 displays the scores across the U.S. states. According to this metrics, Oregon, Illinois, New Jersey, California, and Washington are the states with the most immigrant-protective policies. In contrast, Florida, Texas, and Iowa are the states with the strictest "anti-sanctuary policies." This evidence indicates that the preference for enforcement levels is likely unrelated to previous immigration inflows. For instance, California and Texas are border states and the two largest recipients of immigrants, but they have sharply diverging policy choices on this matter. Iowa is not only far from the border but also counts a negligible low-skill foreign-born population, yet it has one of the most restrictive stands on immigration enforcement.

**Figure 4:** Immigration enforcement across U.S. states




*Note:* This map is constructed by the Immigrant Legal Resource Center (ILRC), which displays the immigration enforcement measures across U.S. states. A higher score (green-colored) indicates a more protective immigration policy. A lower score (purple-colored) indicates a stricter anti-sanctuary policy.

We estimate the following cross-sectional regression using data in 2021: $im_{i,2021} = \alpha + \beta ss_i + \epsilon_i$, where $im_{i,2021}$ is the low-skill immigrant density, and $ss_i$ is the score of sanctuary policies constructed by ILRC. The estimation results are reported in Column (1) of Table 3: low-skill immigrants reside in states with more protective immigration policies. In turn, Column (2) reports the result when the dependent variable is the skill premium. The result shows that sanctuary policies are associated with a higher skill premium. An explanation is that sanctuary policies raise skill premia by increasing low-skill immigrant density (consistent with Fact I).

## 2.4 Fact IV: Educational Attainment is Positively Correlated with the Skill Premium

Lastly, we examine the relation between the skill premium and skill acquisition. To explore this question, we focus on the cohorts of individuals who reside in the same state where they were born and are between the ages of 22 and 26 years old in 2021. Next, we calculate the share of this regional cohort that have a

**Table 3:** Sanctuary policy is positively correlated with low-skill immigration

| | (1) | (2) |
|---|---|---|
| Definition of region | State | |
| Dependent variable | Low-skill immigrant density | Skill premium |
| Sanctuary policy | $0.02^{**}$ | $0.11^{***}$ |
| | (0.01) | (0.04) |
| Constant | -0.01 | $0.34^{***}$ |
| | (0.03) | (0.11) |
| Adj R-squared | 0.08 | 0.13 |
| Observations | 50 | 50 |

*Note:* The dependent variables are low-skill immigrant density and skill premium in 2021 for Columns (1) and (2), respectively. The independent variable is the score of sanctuary policies constructed by ILRC. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

college degree. Our hypothesis is that the decision to pursue post-secondary education in the preceding five years is associated with the payoffs to education at the time of the choice (i.e., the skill premium in 2016) . Two caveats to our assumption. First, we focus on states only since the information for the place of birth is unavailable for metropolitan and commuting-zone areas. Second, since people with different educational attainment can move freely across regions to maximize their expected income, we remove from the sample the workers not living in the same state in which they were born. We denote with $s^C_{i,2021}$ the share of these people who had been to college in the year 2021, and estimate the following regression: $s^C_{i,2021} = \alpha + \beta sp_{i,2016} + \epsilon_i$. Column (1) of Table 4 shows the estimation results. States with higher skill premia encourage more local young people to acquire post-secondary education. In particular, a percentage point rise in skill premium would increase the share of college attainment by 0.12 percentage points, which is an economically significant change.

**Table 4:** Education attainment is positively correlated with skill premium

| Definition of region | State |
|---|---|
| Skill premium | $0.12^{***}$ |
| | (0.03) |
| Constant | $0.38^{***}$ |
| | (0.03) |
| Adj R-squared | 0.15 |
| Observations | 51 |

*Note:* The dependent variable is education attainment in 2021. The independent variables are skill premium and low-skill immigrant density in 2021. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## 2.5 Taking Stock

Fact I suggests the potentially important role of low-skill immigration in the determination of skill premium. Fact II reveals the endogenous nature of immigration to the financial payoff from migrating, which various factors such as productivity levels may drive. Fact III implies that low-skill immigration is heavily influenced by immigration costs, such as penalties incurred from immigration enforcement. Fact IV shows that the skill premium is a critical determinant of investment in education. Facts I and IV jointly imply that low-skill immigration might have a key effect on skill upgrading.

# 3 Model

Our model consists of two large economies (Home and Foreign), and a third small economy (South) that neighbors Home and is the source of low-skill immigrants. In this section, the discussion is focused mainly on the Home and South economies.[12] For Foreign, the equations are similar to those for Home, and its variables are marked with an asterisk.[13] The full derivation of the model is in the Appendix.[14]

## 3.1 Production in the Home Economy

There are two sectors in the Home economy. The first sector produces services, which are non-tradable by definition and require native and immigrant low-skilled labor. This service sector captures the service occupations that require either close contact with the final consumer or need to be executed where the final service is delivered (e.g., childcare or cleaning). The second sector produces a country-specific final good, which is obtained from the aggregation of a continuum of diverse labor tasks. These tasks can be either executed at Home or offshored to Foreign. Workers in this sector are heterogeneous in skill, which they acquire after undergoing training. In short, we will refer to this sector as the "tradable" sector. Notice, however, that the meaning of tradability is different from the one typically encountered in the literature. Here, the tasks needed to produce the final goods, rather than the finals goods themselves, are traded internationally.

**Non-tradable sector.** The first sector produces services that are non-tradable by definition. The labor input used in production, $L^A_{N,t}$, is a CES composite of aggregate units of low-skilled (untrained) native labor, $L_{N,t}$, and immigrant labor, $L^s_{\mathbf{i},t}$:

$$L^A_{N,t} = \left[\alpha \left(L_{N,t}\right)^{\frac{\sigma_N - 1}{\sigma_N}} + (1-\alpha)\left(L^s_{\mathbf{i},t}\right)^{\frac{\sigma_N - 1}{\sigma_N}}\right]^{\frac{\sigma_N}{\sigma_N - 1}}.$$

Output is a linear function of the labor input: $Y_{N,t} = \mathbb{X}_t L^A_{N,t}$. $\mathbb{X}_t$ is a stochastic, permanent world technology shock that affects all productive sectors in all countries. This global shock displays a unit-root which warrants a balanced-growth path for the economy. The price of this service good is $P_{N,t}$. The profit maximization problem implies the following wage equations for low-skill native and immigrant labor: $w_{\mathbf{u},t} = P_{N,t}\mathbb{X}_t\alpha\left(L^A_{N,t}/L_{N,t}\right)^{1/\sigma_N}$ and $w^s_{\mathbf{i},t} = P_{N,t}\mathbb{X}_t(1-\alpha)\left(L^A_{N,t}/L^s_{\mathbf{i},t}\right)^{1/\sigma_N}$.

**Tradable sector.** The tradable sector employs a continuum of skilled workers executing different labor tasks. In order to obtain the skill required for employment in the tradable sector, households invest in training every period. The cost of training involves an irreversible sunk cost, as will be specified later, and results in an idiosyncratic productivity level $\mathbf{z}$ for each worker. Workers draw this idiosyncratic

[12] The appendix describes the system of equations that characterize all the equilibrium conditions of the model as well as the auxiliary equations needed to make the model comparable with the data.

[13] The model is symmetric for Home and Foreign, with the only exception being that Home receives immigrant low-skill labor from the South, whereas Foreign does not. See the appendix for details.

[14] Since we focus on the labor market outcomes from offshoring and immigration, we abstract from capital, hence labor input is the only factor of production.

productivity from a common distribution $\mathcal{F}(\mathbf{z})$ over the support interval $[1, \infty)$ upon completion of training. The untrained (raw) labor provided by each worker is augmented by idiosyncratic productivity $\mathbf{z}$ gained from training and expressed in efficiency units as follows: $l_{\mathbf{z},t} = \mathbf{z}l_t$, where $l_t$ indicates units of raw labor. Idiosyncratic productivity $\mathbf{z}$ remains fixed thereafter until an exogenous skill destruction shock makes the skill obtained from training obsolete, transforming the efficiency units back into units of raw labor. The skill destruction shock is independent of the workers' idiosyncratic productivity level, so $\mathcal{F}(\mathbf{z})$ characterizes the efficiency distribution for all trained native workers at any point in time. The household's training decision is described in more detail further below.

The efficiency units of labor benefit from two technological innovations when used in production. One is the world productivity shock, $\mathbb{X}_t$, and the other is a temporary country-specific technology shock, $\varepsilon_t^Z$. The country-specificic technology shocks and all shocks introduced hereafter evolve as an AR(1) process. As a result, each efficiency unit of labor supplied is transformed in a production task, $n_t(\mathbf{z})$, as follows:

$$n_t(\mathbf{z}) = (\mathbb{X}_t \varepsilon_t^Z) l_{\mathbf{z},t} = (\mathbb{X}_t \varepsilon_t^Z) \mathbf{z} l_t. \tag{1}$$

Trained workers obtain skills and are employed in a variety of occupations, and each of these occupations allows them to execute a given set of tasks $\xi$, which are defined over a continuum of tasks $\Xi$ (i.e., $\xi \in \Xi$). At any given time, only a subset of these tasks $\Xi_t$ ($\Xi_t \subset \Xi$) may be demanded by firms in the global labor market and effectively used in production.[15] The labor input of the tradable sector is obtained by aggregating over a continuum of tasks $n_t(\mathbf{z}, \xi)$ that are imperfect substitutes: $\mathbb{N}_t = \left[\int_{\xi \epsilon \Xi_t} n_t(\mathbf{z}, \xi)^{\frac{\theta-1}{\theta}} d\xi\right]^{\frac{\theta}{\theta-1}}$, where $\theta > 1$ is the elasticity of substitution across tasks. The wage bill is $\mathbb{W}_t = \left[\int_{\xi \epsilon \Xi_t} w_t(\mathbf{z}, \xi)^{1-\theta} d\xi\right]^{\frac{1}{1-\theta}}$, where $w_t(\mathbf{z}, \xi)$ is the wage paid to each efficiency unit of labor. Importantly, some of these tasks may be executed in Foreign, as described in more detail below. With labor as the only input in production, the final tradable good is $Y_{T,t} = \mathbb{N}_t$, and the price of this final good is $P_{T,t} = \mathbb{W}_t$. The price of this tradable good is the numeraire, $P_{T,t} = \mathbb{W}_t \equiv 1$.

**Trade in tasks and the skill income premium.** In a symmetric equilibrium, the wage paid to each worker in the tradable sector is skill-specific. That is, $w_t(\mathbf{z}, \xi) = w_t(\mathbf{z}, .)$ for every task $\xi \in \Xi$. The skill premium $\pi_{D,t}$ in the domestic tradable sector is defined as the difference between the income obtained from a task executed for this sector and the income obtained by a raw unit of labor in the non-tradable sector:

$$\pi_{D,t}(\mathbf{z}, .) = w_{D,t}(\mathbf{z}, .) n_{D,t}(\mathbf{z}, .) - w_{\mathbf{u},t} l_t, \tag{2}$$

where $n_{D,t}(\mathbf{z}, .)$ denotes the task produced by one efficiency unit of labor in the tradable sector for the home market, and $w_{D,t}(\mathbf{z}, .)$ is the associated wage.

Some of the tasks embedded in the Home final good are executed in Foreign and imported (i.e., they are offshored by Home to Foreign). Conversely, Foreign demands some of the tasks executed in Home. Tasks executed in Home and delivered to Foreign, $n_{X,t}(\mathbf{z}, .)$, are paid $w_{X,t}(\mathbf{z}, .)$ and are subject to an

[15] Although workers cannot migrate between Home and Foreign, the labor market of tasks is global as the tasks can be off-shored. In addition, the subset of tasks demanded by foreign companies is $\Xi_t^* \subset \Xi$, and may differ from $\Xi_t$

iceberg offshoring cost $\tau \geqslant 1$ and also to a period-by-period fixed offshoring cost $f_o$, which is defined in terms of efficiency units of labor.[16] Changes in offshoring costs are reflected in shocks $\varepsilon_t^\tau$ to the level of the iceberg cost $\tau$, so that $\tau_t = \varepsilon_t^\tau \tau$. The skill premium, $\pi_{X,t}$, for executing a task for Foreign is:

$$\pi_{X,t}(\mathbf{z},.) = \left(\frac{w_{X,t}(\mathbf{z},.)}{\tau_t} n_{X,t}(\mathbf{z},.) - f_{o,t}\right) - w_{\mathbf{u},t} l_t. \tag{3}$$

All Home workers have their tasks sold domestically. However, due to the iceberg trade cost and the fixed offshoring cost, only the most efficient Home workers engage in multinational production (i.e., execute tasks for both Foreign and Home).[17] A worker will take part in global production as long as the idiosyncratic productivity level $\mathbf{z}$ is above a threshold $\mathbf{z}_{X,t} = \inf\{\mathbf{z} : \pi_{X,t}(\mathbf{z},.) > 0\}$. Conversely, home workers with productivity below $\mathbf{z}_{X,t}$ execute tasks for the domestic market only. To illustrate this idea with an example, consider an scenario in which U.S. multinationals hire professionals from the Silicon Valley area to research, develop and design a state-of-the-art medical device to be sold worldwide. Other tasks may be offshored overseas to exploit comparative advantage (e.g., Chinese programmers develop software, Thai technicians produce flash storage). However, some of the less productive skilled tasks will continue to be produced in-house for the domestic market only, given transportation and communication costs (e.g., customized assembly for U.S. hospitals or help desk services). In this context, a decrease in the offshoring costs allows multinationals to incrementally assign more tasks to foreign workers (e.g. the help desk may reallocate to India when telecommunication costs decrease). Trade integration enhances cross-country task specialization while displacing less skilled workers, and it is consistent with the evidence.[18] Shocks to aggregate productivity, demand, the iceberg trade cost will also result in changes to the threshold level $\mathbf{z}_{X,t}$.[19]

To solve the model with heterogeneous workers, it is useful to define average productivity levels for two representative groups, as in Ghironi and Melitz (2005). First, the average productivity of all workers is: $\tilde{\mathbf{z}}_{D,t} \equiv \left[\int_{\mathbf{1}}^{\infty} \mathbf{z}^{\theta-1} d\mathcal{F}(\mathbf{z})\right]^{\frac{1}{\theta-1}}$. Second, the average efficiency of the workers whose tasks are traded globally is: $\tilde{\mathbf{z}}_{X,t} \equiv \left[\frac{1}{1-\mathcal{F}(\mathbf{z}_{x,t})} \int_{\mathbf{z}_{x,t}}^{\infty} \mathbf{z}^{\theta-1} d\mathcal{F}(\mathbf{z})\right]^{\frac{1}{\theta-1}}$. To derive the average wage and skill premium, it is easier to consider an isomorphic setup where a mass of workers $N_{D,t}$ with average productivity $\tilde{\mathbf{z}}_{D,t}$ execute tasks for the domestic market. Within this group, a mass of high-skilled workers $N_{X,t}$ with average productivity $\tilde{\mathbf{z}}_{X,t}$ accomplish tasks for the foreign market in addition to the domestic market.

[16]The modelling of offshoring costs closely resemble the framework characterizing trade costs in Ghironi and Melitz (2005) For consistency with the economy-wide balanced growth path, this fixed cost is augmented by the world technology shock, then expressed in units of the Home numeraire as follows: $f_{o,t} = \frac{w_{\mathbf{u},t}}{(\mathbb{X}_t \varepsilon_t^Z)}(\mathbb{X}_t f_o)$.

[17]See Krishna et al. (2014) for evidence supporting this result.

[18]Inequality deepens in countries that lower their barriers to trade, irrespective of their degree of economic development. This implication contrasts with that of the traditional Hechsher-Ohlin/Stolper-Samuelson paradigm, which predicts a decrease in the skill premium in countries with abundant low-skilled labor. See Burstein and Vogel (2017) and Goldberg and Pavcnik (2007) for a related discussion.

[19]It is feasible to rationalize a scenario with two countries at different stages of economic development in this context. For instance, the distribution of idiosyncratic productivity in Home may stochastically dominate the one characterizing Foreign –i.e. $\mathcal{F}(\mathbf{z}) > \mathcal{F}^*(\mathbf{z})$. Therefore, workers at the top of the skill distribution in Foreign may have the same productivity as some of the workers in the middle of the skill distribution in Home. Notice, however, that same productivity across countries does not imply same wages in equilibrium. Consistent with the Balassa-Samuelson hypothesis, countries with higher average productivity in the tradable sector pay higher wages to low productivity workers in a sector that is either non-tradable or subject to trade costs. These wage differentials foster the offshoring of tasks despite low productivity in Foreign.

The wages for each skill group are $\tilde{w}_{D,t} = w_{D,t}(\tilde{\mathbf{z}}_{D,t},.)$ and $\tilde{w}_{X,t} = w_{X,t}(\tilde{\mathbf{z}}_{X,t},.)$. Combining all these, the wage bill of the home tradable sector can be re-written as: $\mathbb{W}_t = \left[N_{D,t}\left(\tilde{w}_{D,t}\right)^{1-\theta} + N^*_{X,t}\left(\tilde{w}^*_{X,t}\right)^{1-\theta}\right]^{\frac{1}{1-\theta}}$, where $N^*_{X,t}$ denotes foreign workers executing tasks imported by Home, and $\tilde{w}^*_{X,t}$ is the corresponding wage expressed in units of the Home numeraire. The skill premia for each group are $\tilde{\pi}_{D,t} = \pi_{D,t}(\tilde{\mathbf{z}}_{D,t},.)$ and $\tilde{\pi}_{X,t} = \pi_{X,t}(\tilde{\mathbf{z}}_{X,t},.)$. Finally, the average skill premium is defined as: $\pi_t = (N_{D,t}\tilde{\pi}_{D,t} + N_{X,t}\tilde{\pi}_{X,t})/N_{D,t}$. By assumption, low-skilled labor is only used in non-tradable services.

### 3.2 Households in the Home Economy

Household members form an extended family and pool their labor income – obtained from working in the tradable and non-tradable sectors – and choose aggregate variables to maximize expected lifetime utility. As in Andolfatto (1996), the model assumes that household members perfectly insure each other against fluctuations in labor income resulting from changes in their employment status. This assumption eliminates any type of ex-post heterogeneity across workers at then household level.

**Consumption.** Household's consumption basket is:

$$C_t = \left[(\gamma_c)^{\frac{1}{\rho_c}}\left(C_{T,t}\right)^{\frac{\rho_c-1}{\rho_c}} + (1-\gamma_c)^{\frac{1}{\rho_c}}\left(C_{N,t}\right)^{\frac{\rho_c-1}{\rho_c}}\right]^{\frac{\rho_c}{\rho_c-1}},$$

which includes amounts of the tradable good $C_{T,t}$ and the non-tradable services $C_{N,t}$. The consumer price index is: $P_t = \left[\gamma_c + (1-\gamma_c)\left(P_{N,t}\right)^{1-\rho_c}\right]$. The final good produced in the tradable sector in Home, $Y_{T,t}$, is a composite of domestic and foreign tasks. It is entirely used for consumption by the Home household, $C_{T,t}$, and also by the Southern immigrant workers established in Home, $C^s_{T,t}$, so that $Y_{T,t} = C_{T,t} + C^s_{T,t}$. The problem of the Southern household is described in Section 3.3.

**Household's problem.** The household has standard additive separable utility over real consumption, $C_t$, and leisure, $1 - L_t$, where $L_t$ is the aggregate supply of raw labor. By choosing consumption, labor, training, and bond holdings, the Home representative household maximizes a standard utility kernel, which is modified to be consistent with the balanced growth-path:

$$\mathbb{E}_t\sum_{s=t}^{\infty}\beta^{s-t}\varepsilon^b_t\left[\frac{1}{1-\gamma}C_t^{1-\gamma} - a_n\mathbb{X}_t^{1-\gamma}\frac{L_t^{1+\gamma_n}}{1+\gamma_n}\right], \tag{4}$$

where parameter $\beta \in (0,1)$ is the subjective discount factor, $\gamma > 0$ is the inter-temporal elasticity of substitution, $\gamma_n > 0$ is the inverse of the Frisch elasticity of labor supply, and $a_n > 0$ is the weight on the disutility from labor. Also, $\varepsilon^b_t$ is a shock to the intertemporal rate of substitution, which may be interpreted as a consumption demand shock.

The period budget constraint expressed in units of the numeraire good is:

$$w_{\mathbf{u},t}L_t + \pi_t N_{D,t} = f_{j,t}N_{E,t} + P_tC_t + q_tB_t - B_{t-1} + \Phi(B_t). \tag{5}$$

Total income is captured by the two terms of the left-hand side. The first term, $w_{\mathbf{u},t}L_t$, captures the remuneration of all raw units of labor, which includes the income of low-skilled labor employed in the non-tradable service sector, as well as the "shadow" income generated by the raw labor that undergoes training and works in the tradable sector. The second term captures the total skill income premium that results from training and selling tasks domestically, defined as the product between the total measure of skilled workers, $N_{D,t}$, and their average skill income premium, $\pi_t$ as defined above.

On the right-hand side of (5), the first term represents the total investment in training, in which $N_{E,t}$ are the new skilled occupations created at time $t$, and $f_{j,t}$ is the sunk training cost required for each of these new skilled workers. Training costs are time-varying and are subject to cost-push shocks $\varepsilon_t^{Tr}$ such that: $f_{j,t} = \left(\varepsilon_t^{Tr} f_j\right)^{\Theta_{f_j}}$ , where $\Theta_{f_j}$ is defined as the elasticity of total training costs to observed tuition costs, which will be estimated below. Like offshoring costs, these costs also require a path consistent with balanced-growth.[20] International financial transactions are restricted to a one-period, risk free bond. The level of debt due every period is $B_{t-1}$, and the new debt contracted is $B_t$ at price $q_t = 1/(1 + r_t)$, with $r_t$ representing the implicit interest rate. To induce model stationarity in balanced-growth, we introduce an arbitrarily small cost of debt, $\Phi(B_t) = \mathbb{X}_t \frac{\phi}{2}\left(\frac{B_t}{\mathbb{X}_t}\right)^2$.

**Measure of skilled workers.** The newly-created skilled workers $N_{E,t}$ join the already-existing $N_{D,t}$ with a time-to-build lag, and together are subject to a skill destruction shock $\delta$, that renders the skills obtained from training obsolete. Therefore, the resulting law of motion for the skilled occupations is: $N_{D,t} = (1 - \delta)(N_{D,t-1} + N_{E,t-1})$, where we assume that new skilled workers start working at $t + 1$.

**Optimality conditions.** The household maximizes utility subject to its budget constraint and the law of motion for skilled workers described above. The optimality conditions for labor effort and consumption/saving are conventional:

$$\hat{a}_n \left(L_t\right)^{\gamma_n} \left(C_t\right)^{\gamma} = \frac{w_{\mathbf{u},t}}{P_t}, \tag{6}$$

$$q_t = \beta E_t \left\{ \frac{\zeta_{t+1}}{\zeta_t} \right\} - \Phi'(B_t), \tag{7}$$

where $\hat{a}_n = a_n \mathbb{X}_t^{1-\gamma}$, and $\zeta_t = \varepsilon_t^b (C_t)^{-\gamma}/P_t$ characterizes the marginal utility of consumption. The optimality governing the choice of bonds for foreign households in conjunction with the Euler equation in (7) yields the following risk-sharing condition:

$$E_t \left\{ \frac{\zeta_{t+1}^*}{\zeta_t^*} \frac{\mathbb{Q}_t}{\mathbb{Q}_{t+1}} - \frac{\zeta_{t+1}}{\zeta_t} \right\} = -\frac{\Phi'(B_t)}{\beta}, \tag{8}$$

[20] This sunk cost is expressed in units of the numeraire good as: $\tilde{f_{j,t}} = \frac{w_{\mathbf{u},t}}{(\mathbb{X}_t \varepsilon_t^Z)}(\mathbb{X}_t f_{j,t})$.

where $\mathbb{Q}_t$ is the factor-based real exchange rate (or terms of labor).[21] Finally, the optimality condition for training is pinned down by the following condition:

$$f_{j,t} = \mathbb{E}_t \sum_{s=t+1}^{\infty} \left[\beta \left(1-\delta\right)\right]^{s-t} \left(\frac{\zeta_s}{\zeta_t}\right) \tilde{\pi}_s, \tag{9}$$

This equation shows that in equilibrium the sunk training cost $f_{j,t}$ equals the present discounted value of the future skill premia resulting from the creation of a new skilled occupations $\{\tilde{\pi}_s\}_{s=t+1}^{\infty}$ adjusted for the probability of skill destruction $\delta$.

### 3.3 South Economy

The representative household in South provides raw labor without the possibility of training. This labor can either be employed in domestic production or emigrate to Home after incurring a sunk migration cost. The household members pool their total income, which is obtained from both domestic and emigrant labor, and choose aggregate variables to maximize lifetime utility.

**Labor migration.** The representative household supplies a total of $L^s_{\mathbf{u},t}$ units of raw labor every period. A portion of the household members $L^s_{\mathbf{i},t}$ reside and work as low-skill immigrant workers abroad (in Home). The remaining $L^s_{\mathbf{u},t} - L^s_{\mathbf{i},t}$ work in the country of origin (in South). The calibration ensures that the low-skill wage in Home is higher than the wage in South, so that the incentive to emigrate from South to Home exists every period. However, a fraction of total labor supply always remains in South ($0 < L^s_{\mathbf{i},t} < L^s_{\mathbf{u},t}$). The macroeconomic shocks are small enough for these conditions to hold in every period.

The household sends an amount $L^s_{\mathbf{e},t}$ of new emigrant labor to Home every period, where the stock of immigrant labor $L^s_{\mathbf{i},t}$ is built gradually over time. The time-to-build assumption in place implies that the new immigrants start working one period after arriving. They continue to work in all subsequent periods until a return-inducing exogenous shock, which hits with probability $\delta_l$ every period, forces them to return to South. This shock reflects issues such as termination of employment in the destination economy, deportation, or voluntary return to the country of origin, etc.[22] The resulting rule of motion for the stock of immigrant labor in Home is: $L^s_{\mathbf{i},t} = (1-\delta_l)(L^s_{\mathbf{i},t-1} + L^s_{\mathbf{e},t-1})$.

**Household's decision problem.** By choosing consumption, labor, and immigration, the South representative household maximizes maximizes lifetime utility:

$$\mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \left[ \frac{1}{1-\gamma} (C^s_t)^{1-\gamma} - a^s_n \mathbb{X}_t^{1-\gamma} \frac{(L^s_{\mathbf{u},t})^{1+\gamma_n}}{1+\gamma_n} \right], \tag{10}$$

[21]That is, $\mathbb{Q}_t = \frac{\varepsilon \mathbb{W}^*_t}{\mathbb{W}_t}$. Thus, the real exchange rate is expressed in units of the foreign numeraire per units of the home one, where $\varepsilon$ is the nominal exchange rate.

[22]Our endogenous emigration-exogenous return formulation is similar to the framework with firm entry and exit in Ghironi and Melitz (2005).

subject to the law of motion for immigrant labor and the budget constraint:

$$w_{\mathbf{i},t}^{s}L_{\mathbf{i},t}^{s}+w_{\mathbf{u},t}^{s}\left(L_{\mathbf{u},t}^{s}-L_{\mathbf{i},t}^{s}\right)\geqslant f_{e,t}L_{\mathbf{e},t}^{s}+P_{t}^{s}C_{t}^{s}, \tag{11}$$

where $w_{\mathbf{i},t}^{s}$is the immigrant wage earned in Home (the same as the low-skilled wage), so that the emigrant labor income is $w_{\mathbf{i},t}^{s}L_{\mathbf{i},t}^{s}$. Also, $w_{\mathbf{u},t}^{s}$ is the wage earned in South, so that $w_{\mathbf{u},t}^{s}\left(L_{\mathbf{u},t}^{s}-L_{\mathbf{i},t}^{s}\right)$ denotes the total income from hours worked by the non-emigrant labor. On the spending side, each new unit of emigrant labor sent to Home requires a sunk cost $f_e$, expressed in units of immigrant labor: $f_{e,t}=\frac{w_{\mathbf{i},t}}{(\mathbb{X}_t\varepsilon_t^Z)}(\varepsilon_t^{fe}\mathbb{X}_t f_e)$. Changes in labor migration policies (i.e. border enforcement) are reflected by shocks $\varepsilon_t^{fe}$ to the level of the sunk emigration cost $f_e$. Consumption of the South household, $C_t^s$, is a CES composite of non-tradables produced in South, $C_{N,t}^s$, and the Home tradable composite $C_{T,t}^s$ which may account for immigrants' consumption in Home, as well as imports from Home to South.[23] $P_t^s$ is the resulting consumer price index.

**Optimality conditions.** The optimization problem delivers the typical conditions for consumption and labor supply. Using the law of motion for the stock of immigrant labor, the first order condition with respect to new emigrants $L_{\mathbf{e},t}^s$ implies:

$$f_{e,t}=\mathbb{E}_t\sum_{s=t+1}^{\infty}\left[\beta(1-\delta_l)\right]^{s-t}\left(\frac{\zeta_s^s}{\zeta_t^s}\right)(w_{\mathbf{i},t}^{s}-w_{\mathbf{u},t}^{s}). \tag{12}$$

In equilibrium, the sunk emigration cost, $f_{e,t}$, equals the benefit from emigration, with the latter given by the expected stream of future wage gains from working abroad vis-a-vis home (i.e. $w_{\mathbf{i},t}^{s}-w_{\mathbf{u},t}^{s}$) adjusted for the stochastic discount factor and the probability of return to the country of origin every period, $\delta_l$.

**Non-tradable sector.** Southern output is non-tradable and obtained as a linear function of non-emigrant labor: $Y_{N,t}^s=(\varepsilon_t^s\mathbb{X}_t)\left(L_{\mathbf{u},t}^{s}-L_{\mathbf{i},t}^{s}\right)$. Here, $\mathbb{X}_t$ is the unit-root global technology shock and $\varepsilon_t^s$ is a country-specific shock. The price of the non-tradable good is: $P_{N,t}^s=\frac{w_{\mathbf{u},t}^s}{\mathbb{X}_t\varepsilon_t^s}$. By definition, $Y_{N,t}^s=C_{N,t}^s$. [24]

[23] We consolidate the current account for Home and Foreign and abstract from modelling migrants' remittances which, in principle, could be used to finance these imports.

[24] For simplicity, we define a consolidated current account for Home and South. Thus, the evolution of the net foreign asset position for this artificial economy is:

$$q_tB_t-B_{t-1}=N_{X,t}\left(\tilde{w}_{X,t}\right)^{1-\theta}N_t^*\mathbb{Q}_t-N_{X,t}^*\left(\tilde{w}_{X,t}^*\right)^{1-\theta}N_t, \tag{13}$$

where, on the right-hand side, the first term is the sum of all tasks executed by home skilled workers and exported to Foreign, and the second term represents the tasks executed by foreign skilled workers and imported in Home, expressed in units of the home numeraire. This trade in tasks is one of the key characteristics of this model. The Home and Foreign risk-free bonds are in zero net supply: $B_t+B_t^*=0$. Our model is propagated by nine shocks: shocks to Global ($\mathbb{X}_t$), Home ($\epsilon_t^Z$), Foreign ($\epsilon_t^{Z^*}$), and South technology ($\epsilon_t^s$); shocks to demand in Home ($\epsilon_t^b$) and Foreign ($\epsilon_t^{b^*}$); shocks to iceberg offshoring cost ($\tau_t$), training cost ($\epsilon_t^{Tr}$), and sunk emigration cost ($f_{e,t}$). The world technology shock has a unit root, as in Rabanal et al. (2011): $\log\mathbb{X}_t=\mathbb{X}_{t-1}+\eta_t^{\mathbb{X}}$. The other structural shocks in our model follow $AR(1)$ processes with i.i.d. normal error terms, $\log\varepsilon_t^{\hat{\imath}}=\rho^{\hat{\imath}}\log\varepsilon_{t-1}+\eta_t^{\hat{\imath}}$, in which the persistence parameter is $0<\rho^{\hat{\imath}}<1$. The error terms are $\eta\sim N(0,\sigma^{\hat{\imath}})$, and indexes $\hat{\imath}=\{\mathbb{X},Z,Z^*,s,b,b^*,\tau,f_e,Tr\}$ denote the shocks. Country specific shocks are independent.

# 4 Data and Estimation

We estimate the model with the Bayesian approach that uses the full set of system equations, thus avoiding the potential identification issues of reduced form models. The approach combines the prior distribution on the estimated parameters with the likelihood function of the solved DGSE model to obtain posterior distribution of the structural parameters. This section describes the prior and posterior distributions of the parameters.[25]

**Data.** We estimate the model using eight quarterly series for the sample period 1983:Q1 – 2018:Q4.[26] With the sample period ending in 2018:Q4, we abstract from a set of unprecedented events in recent quarters, which include the spike in border apprehensions in 2019 of the COVID-19 pandemic, which triggered an immediate collapse in employment and output prompted by lockdown measures, as well as as a sharp pickup in apprehensions in the aftermath of the late 2018 known as the migrant caravans and the post-pandemic years. Nonetheless, we use the estimated parameters to analyze the welfare implications of those severe events in our policy application in Section 6.

The first three series are output for the Home, Foreign, and South economies. We use U.S. real GDP as a proxy for Home output; for Foreign we construct as a trade-weighted GDP aggregate of the U.S. major trade partners; and South output is proxied by Mexico's real GDP.

The fourth observable is the total U.S. patrol hours at the U.S./Mexico border, shown in Figure 5, which serves as a proxy for the intensity of border enforcement and the restrictiveness of immigration policy more generally. An increase in border patrol hours is interpreted as an increase in the sunk migration cost, as in Mandelman and Zlate (2012).

The fifth to seventh observables are the per-capita employment for three skill groups (high-skill, middle-skill, and low-skill service occupations) in the U.S. which are measured with a similar approach to Acemoglu and Autor (2011) and Jaimovich and Siu (2020).[27]

The final observable series consists of real tuition costs, defined as tuition, other school fees, and childcare deflated by the total consumer price index (CPI), which is the data counterpart for the sunk training cost in the model. Importantly, we allow for the sunk training cost to not necessarily be linked to its data counterpart in a linear fashion; instead, we let the data pin down the value of the elasticity

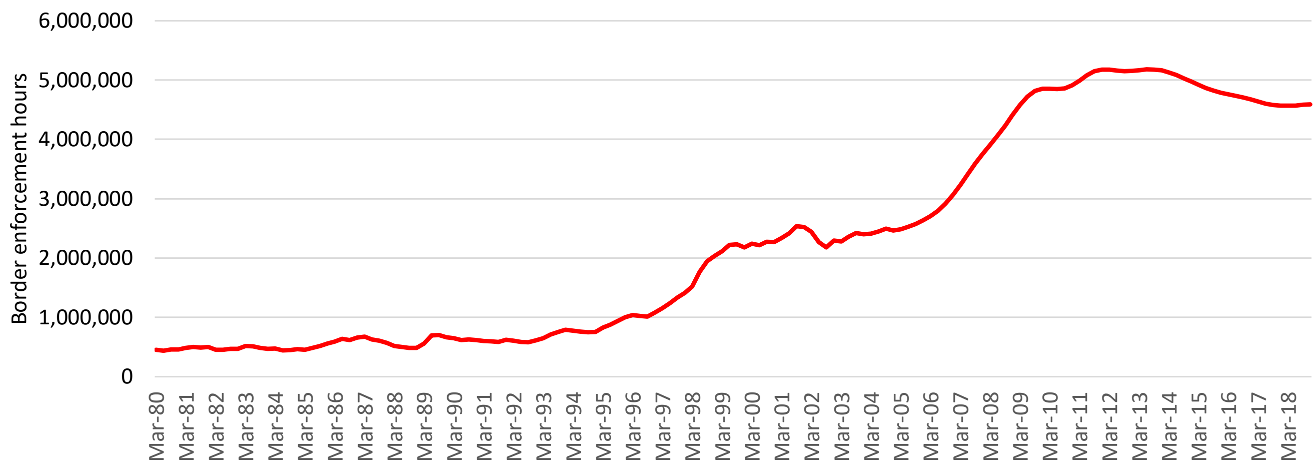
[25]See the appendix for detailed information on data sources and the estimation methodology. An and Schorfheide (2007) and Mandelman and Zanetti (2014) for an overview and implementation of the Bayesian estimation. In addition, the appendix includes a description of the smoothing procedure implemented with the Kalman filter, the Monte Carlo Markov Chain (MCMC) convergence diagnostics, and the Bayes Factor used for model comparison.

[26]We use eight data series while the model has eight shocks, hence the number of data series used in the estimation does not exceed the number of shocks, avoiding stochastic singularity.

[27]The U.S. Census employment data discussed in the introduction is decennial and thus not available on a high-frequency basis. In addition, it cannot be split easily into the three skill groups. We construct employment by skill group using data from the Current Population Survey (CPS). We consider three categories of employment based on the skill content of the tasks executed by each occupation in the Census data: Non-Routine Cognitive (high-skill), Routine Cognitive (middle-skill) and Non-Routine Manual (low-skill). Notice, that in the estimation we use total employment over population for each skill group while the introduction illustrates changes in employment shares in the Census data. In Jaimovich and Siu (2020) construction occupations are grouped with the middle-skill segment. We take a different approach for two reasons. First, construction is non-tradable by definition. Second, even though the earnings for the registered workers belong to the middle of the skill distribution. The underground economy is pervasive in this sector, and most low-skill laborers in this sector remain unregistered. See the data appendix for more details.

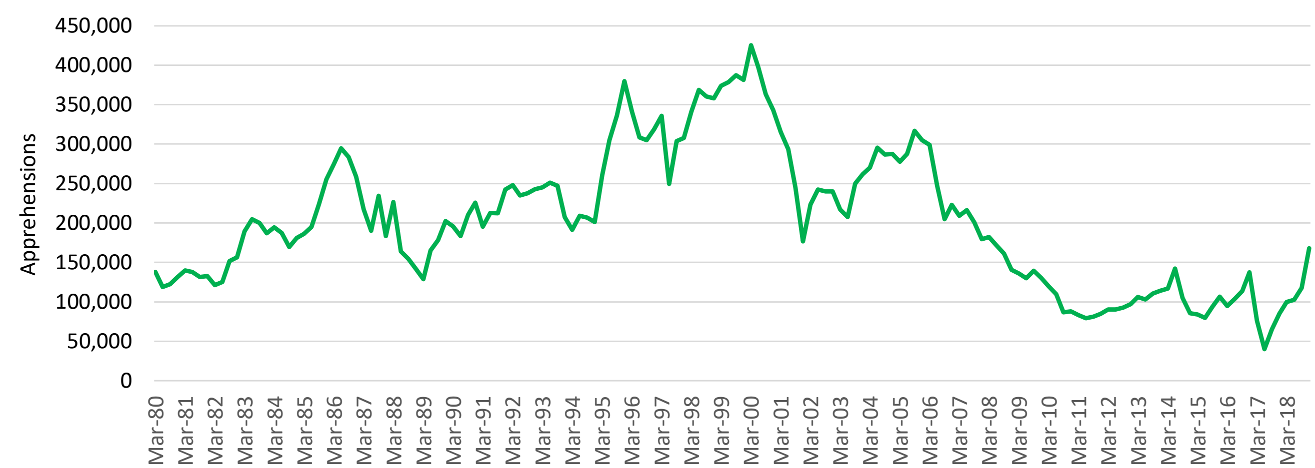
of the sunk training cost to the real tuition cost series as defined in the model description. Finally, all series used for model estimation are seasonally adjusted and expressed in log-differences to obtain growth rates.[28]

**Figure 5:** U.S. border patrol enforcement at the U.S.-Mexico border




*Note:* This chart shows the number of border enforcement hours at the U.S.-Mexico border as a proxy for the restrictiveness of immigration policy. The data are from the U.S. Immigration and Naturalization Service (INS) for 1980-2004 (linewatch enforcement hours), used in Hanson and Spilimbergo (1999) and Hanson (2006), which we supplement with more recent data from the U.S. Customs and Border Protection (border patrol agent staffing at the Southern border).

**Figure 6:** Apprehensions at the U.S.-Mexico border




*Note:* This figure illustrates the number of apprehensions (arrests) at the U.S.-Mexico border as a proxy for the inflows of low-skill undocumented immigrant labor. The data are from the U.S. Customs and Border Protection for 2000-2018 (U.S. apprehensions at the Southwest border), which we supplement with earlier data from the U.S. Immigration and Naturalization Service (INS) for 1980-1999 used in Hanson and Spilimbergo (1999) and Hanson (2006) (linewatch apprehensions).

Two important variables are not used in the model estimation: (a) the inflows of low-skill migrant

[28] The real GDP and tuition cost series are not detrended, while border enforcement is constructed as deviations from a linear trend. Along the balanced growth path in the model, border enforcement should grow at the same rate as output and tuition costs. Therefore, we follow Adolfson et al. (2007) and rend border enforcement stationary by detrending its empirical counterpart around a linear trend.

workers, and (b) the cost of offshoring. They do not enter the estimation for separate reasons. For the inflows of low-skill migrant workers, a large number of them arrive illegally and remain undocumented, hence it can only be regarded as an accurate but noisy proxy for these flows when measured at short-run frequencies. In particular, the number of individuals apprehended by U.S. patrol officers in attempting to illegally cross the U.S./Mexico border, shown in Figure 6, serves as a proxy for the inflow of low-skill migrant workers. As pointed out in Hanson and Spilimbergo (1999), *ceteris paribus*, an increase in unauthorized immigration would lead to more border apprehensions. Nonetheless, the latter represent an imperfect indicator for immigration flows due to their complex relation with the intensity of border enforcement. Higher enforcement may discourage attempted unauthorized immigration, but for a given number of crossing attempts, higher enforcement can also result in more apprehensions. To address this issue, Hanson and Spilimbergo (1999) use instrumental variables methods to account for unauthorized immigration inflows, which result in the following reduced form specification: $ln(\text{Apprehensions}) - 0.8 \times ln(\text{OfficerHours})$. We adopt their approach and use this measure as a proxy for migration flows.

The cost of offshoring is affected not only by changes in trade costs, but also by advances in telecommunications. These advances facilitate breaking down the production process in different locations as they allow workers in distant places to interact and monitor each other in real-time. Even tough language and communication barriers are indirectly included in the ESCAP/ World Bank trade cost measure, it is not feasible, however, to directly quantify the impact of these technological advancements on the actual cost of offshoring tasks. Therefore, the two variables are not directly considered in the model estimation but are used to evaluate the empirical adequacy of the model predictions by comparing them to the empirical proxies.

**Prior distributions.** We estimate the set of parameters shown in Table 5.[29] The density functions of the prior probability are centered at the values described below and entail the size of the standard deviation that delivers a domain suitable to cover a wide range of empirically plausible parameter values. Shocks are harmonized with a very loose prior since we do not have much prior information about their magnitude. Some of these parameter values remain fixed through the estimation procedure, which can be interpreted as a prior that is extremely precise. Our procedure is necessary to address identification issues arising from the limited number of variables used in the estimation.

We use six empirical moments as targets to parameterize the prior values of six key model parameters affecting offshoring and labor migration. These moments include: (1) the ratio of high- to middle-skill jobs in the U.S. of 0.6; (2) the ratio between the high- and middle-skill labor income shares in the total U.S. labor income of 1.7;[30] (3) the share of low-skill workers in the native U.S. labor force of 0.2; (4) the

[29] Model parameters are assumed to follow a `Gamma` distribution with a positive domain $[0,\infty)$. The auto-regressive parameters for the stationary shocks are assumed to follow a `Beta` distribution, which covers the range between 0 and 1. The standard deviation of all stochastic processes is assumed to follow an `InverseGamma` distribution that delivers a relatively large domain.

[30] The CPS survey reports the money income that includes wages and salaries, interest, dividends, rent, retirement income, as well as other transfers. There is one crucial caveat. Our basic model abstracts from capital, so it is difficult to map each of these income sources to the skill groups defined in our setup. In addition, the CPS survey data are not suitable for studying high-income groups because of the small sample size and top coding of high incomes.

ratio between U.S. low-skill wages and wages in Mexico of 2.2;[31] (5) the ratio of U.S. exports to GDP of 0.13; and (6) the ratio of U.S.-to-Mexico per-capita GDP of 5.4.

Regarding the associated six model parameters, we loosely center the prior distribution for sunk emigration cost at $f_e = 8.8$, while fixing the quarterly return rate of immigrant labor at $\delta_l = 0.05$, which is consistent with the data in Reyes (1997).[32] Following a similar strategy, we center the prior distribution for the iceberg offshoring costs at $\tau = \tau^* = 1.40$, consistent with Novy (2018), while fixing the cost of offshoring at $f_o = f_o^* = 0.0155$ to get identification while matching export ratios. The prior distribution for the elasticity of total training costs to observed tuition costs is centered at $\Theta_{f_j} = 0.35$, while the sunk training cost is normalized at $f_j = 1$ and the quarterly job-destruction rate is fixed at $\delta = 0.025$ as in Davis and Haltiwanger (1990). The response of labor supply to aggregate conditions is critical for the quantitative analysis, so we center the prior for $\gamma_n$ and $\gamma_n^s$ at 1.33, consistent with the micro estimates for the Frisch Elasticity in Chetty (2012).[33]

**Calibration.** The remaining parameters are calibrated using standard values. Consistent with Borjas et al. (2008), the baseline specification assumes perfect substitution between native and low-skilled immigrant workers, so $\sigma_N$ is set at an arbitrarily very high value. This choice is somewhat controversial since other authors like Ottaviano and Peri (2012) find instead that the labor inputs tend to be complementary. We discuss the implications of this alternative scenario in Section 6. We set standard values for $\beta = 0.99$ and the inverse of the elasticity of inter-temporal substitution, $\gamma = 2$. [34] The idiosyncratic productivity of workers $\mathbf{z}$ follows the Pareto distribution $\mathcal{F}(\mathbf{z}) = 1 - \left(\frac{1}{\mathbf{z}}\right)^k$, like in Hamano and Zanetti (2017) .[35] The shape parameter is $k = 3.1$, and the elasticity of substitution across tasks in Home and Foreign is fixed at $\theta = 2.4$. to match the skewed U.S. income distribution.[36]

**Estimation results, posterior distributions.** The last four columns of Table 5 report the posterior mean, mode, as well as the 10th and 90th percentiles of the posterior distribution of the parameters. Prior and posterior densities are displayed in the appendix. The posterior mean of the sunk emigration cost, $f_e$, is equivalent to the immigrant labor income obtained over seven quarters in the destination economy. This value is only slightly higher than the estimate of five quarters found in Mandelman and

[31] BLS and INEGI are the data sources, for the U.S. and Mexico, respectively. For the U.S., we consider median labor earnings for males with less than a high-school degree. For Mexico, we take the median wage for males.

[32] Reyes (1997) studies the return pattern of undocumented Mexican immigrants. They find that approximately only 50% remain in the U.S. after 2 years. Similarly, 35%, 25%, and 20% of them remain after 4, 10, and 15 years, respectively. We construct quarterly return rates based on these numbers. The resulting average is 0.05.

[33] The weights on the disutility from work are centered at $a_n = 3.9$ in Home and Foreign and $a_n^s = 8.6$ in the South, such that per-capita labor supply for each region is normalized to the data moments previously described along balanced growth.

[34] The cost of adjusting bond holdings is set at a very low value, $\phi = 0.0035$, which is sufficient to ensure stationarity. Per-capita labor supply is normalized in balanced-growth at $L_t = L_t^* = L_{\mathbf{u},t}^s = 0.5$. The share of tradable consumption is $\gamma_c = 0.75$ and the intra-temporal elasticity of substitution between the tradables and services is set at $\rho_c = 0.44$ as in Stockman and Tesar (1995). In the South, the share of the Home-produced tradable good $\gamma_c^s$ in Household consumption is 0.2, the associated elasticity of substitution is $\rho_c^s = 1.5$.

[35] The shape parameter $k$ is such that $k > \theta - 1$ so that $\mathbf{z}$ has a finite variance. When the parameter $k$ is set at higher values, the dispersion of the productivity draws decreases and the idiosyncratic productivity becomes more concentrated toward the lower bound of the skill distribution.

[36] Notice, however, that the interpretation for some of these parameters may differ from the literature, since our framework features tradable *tasks* rather than tradable *goods*, and skill obsoletion rather than job destruction.

**Table 5:** Prior and Posterior distributions for estimated parameters

| | Prior distribution | | | | Posterior distribution | | | |
|---|---|---|---|---|---|---|---|---|
| Description | Name | Density | Mean | Std Dev | Mode | Mean | 10% | 90% |
| Sunk training cost elasticity | $\Theta_{f_j}$ | Beta | 0.35 | 0.05 | 0.1927 | 0.1979 | 0.1639 | 0.2341 |
| Sunk emigration cost | $f_e$ | Gamma | 8.8 | 0.1 | 7.2320 | 7.3579 | 6.4824 | 8.2679 |
| Iceberg offshoring cost (H) | $\tau$ | Gamma | 1.4 | 0.15 | 1.4141 | 1.3920 | 1.2399 | 1.5521 |
| Iceberg offshoring cost (F) | $\tau^*$ | Gamma | 1.4 | 0.15 | 1.4816 | 1.5014 | 1.3786 | 1.6268 |
| Inv. elast. labor supply (H) | $\gamma_n$ | Gamma | 1.33 | 0.3 | 1.0768 | 1.1997 | 0.9604 | 1.4838 |
| Weight disutility work (H) | $a_n$ | Gamma | 3.9 | 0.3 | 4.0379 | 4.0037 | 3.6298 | 4.3699 |
| Inv. elast. labor supply (S) | $\gamma_n^s$ | Gamma | 1.33 | 0.3 | 1.0634 | 1.1439 | 0.8200 | 1.4873 |
| Weight disutility work (S) | $a_n^s$ | Gamma | 8.6 | 1 | 8.5748 | 8.6473 | 7.4334 | 9.8875 |
| Training cost shock | $\rho_{f_j}$ | Beta | 0.75 | 0.1 | 0.9988 | 0.9983 | 0.9974 | 0.9990 |
| Migration cost shock | $\rho_{f_e}$ | Beta | 0.75 | 0.1 | 0.9802 | 0.9786 | 0.9676 | 0.9885 |
| Offshoring cost shock | $\rho_\tau$ | Beta | 0.75 | 0.1 | 0.9918 | 0.9894 | 0.9831 | 0.9948 |
| Technology shock (H) | $\rho_Z$ | Beta | 0.75 | 0.1 | 0.9973 | 0.9966 | 0.9946 | 0.9983 |
| Technology shock (F) | $\rho_{Z^*}$ | Beta | 0.75 | 0.1 | 0.7123 | 0.7057 | 0.6506 | 0.7582 |
| Technology shock (S) | $\rho_{Z^s}$ | Beta | 0.75 | 0.1 | 0.9961 | 0.9944 | 0.9903 | 0.9977 |
| Demand shock (H) | $\rho_b$ | Beta | 0.5 | 0.05 | 0.7806 | 0.7659 | 0.7410 | 0.7861 |
| Demand shock (F) | $\rho_{b^*}$ | Beta | 0.5 | 0.05 | 0.4995 | 0.4989 | 0.4297 | 0.5657 |
| Training cost shock | $\sigma_{f_j}$ | Inv gamma | 0.01 | 2* | 0.0117 | 0.0119 | 0.0110 | 0.0128 |
| Migration cost shock | $\sigma_{f_e}$ | Inv gamma | 0.01 | 2* | 0.0285 | 0.0288 | 0.0266 | 0.0310 |
| Offshoring cost shock | $\sigma_\tau$ | Inv gamma | 0.01 | 2* | 0.0059 | 0.0061 | 0.0055 | 0.0069 |
| Technology shock (H) | $\sigma_Z$ | Inv gamma | 0.01 | 2* | 0.0530 | 0.0532 | 0.0491 | 0.0575 |
| Technology shock (F) | $\sigma_{Z^*}$ | Inv gamma | 0.01 | 2* | 0.0287 | 0.0303 | 0.0261 | 0.0348 |
| Technology shock (S) | $\sigma_{Z^s}$ | Inv gamma | 0.01 | 2* | 0.0542 | 0.0538 | 0.0487 | 0.0591 |
| Demand shock (H) | $\sigma_b$ | Inv gamma | 0.01 | 2* | 0.0155 | 0.0158 | 0.0146 | 0.0172 |
| Demand shock (F) | $\sigma_{b^*}$ | Inv gamma | 0.01 | 2* | 0.0040 | 0.0047 | 0.0030 | 0.0068 |
| Global technology shock | $\sigma_{\mathbb{X}}$ | Inv gamma | 0.01 | 2* | 0.0290 | 0.0290 | 0.0268 | 0.0312 |

*Note:* The table shows the prior and posterior distributions of the model parameters subject to Bayesian estimation. (*) For the Inverse Gamma the degrees of freedom are reported.

Zlate (2012), which was based on a shorter time series for border enforcement (1983-2004). The elasticity of the sunk training cost to the observed real tuition costs, $\Theta_{fj}$, is relatively low, which could reflect the possibility of substitution from private to public education or to alternative career paths with similar earning payoffs but lower education costs, which we do not model here. Productivity shocks are relatively more persistent than demand shocks, which is consistent with the literature (e.g. Smets and Wouters, 2007). Offshoring costs are very persistent and relatively less volatile than the stochastic innovations to border enforcement. Real tuition costs display near unit-root dynamics.

# 5 Model Fit and the Effect of Shocks

In this section, we study the fit of the model to the data, the propagation of shocks to a decline in migration, training, and offshoring costs, and we provide the historical contribution of the estimated shocks to key economic variables over the period 1983-2018.

## 5.1 Model Fit

We proceed with the posterior predictive analysis that compares the actual data with artificial time series generated with our estimated model. As already discussed, we do not use data series on immigrant flows or offshoring costs to estimate the model. Instead, we treat immigrant entry ($L_{e,t}$) and the iceberg offshoring cost ($\tau_t$) as latent variables in the estimated model and we can use the comparison of them with data to assess the model fit. For this purpose, the Kalman filter provides smoothed estimated shocks to construct the predictions for the unobserved variables in each period, which allows for the reconstruction of the artificial historical series.[37] Figure 7(A) shows model predictions for the flows of low-skill immigrant labor, expressed as deviations from balanced-growth (dashed line) together with their empirical detrended proxy for migration adjusted for border enforcement like in Hanson and Spilimbergo (1999) and Hanson (2006) (solid line). The model predictions are broadly consistent with the data, despite the final years of the sample being remarkably noisy. This likely reflect the documented changes in seasonal pattern in unauthorized immigration after 2013 (see Gramlichv and Scheller, 2021) which are missed by the standard seasonal adjustment methods.[38]

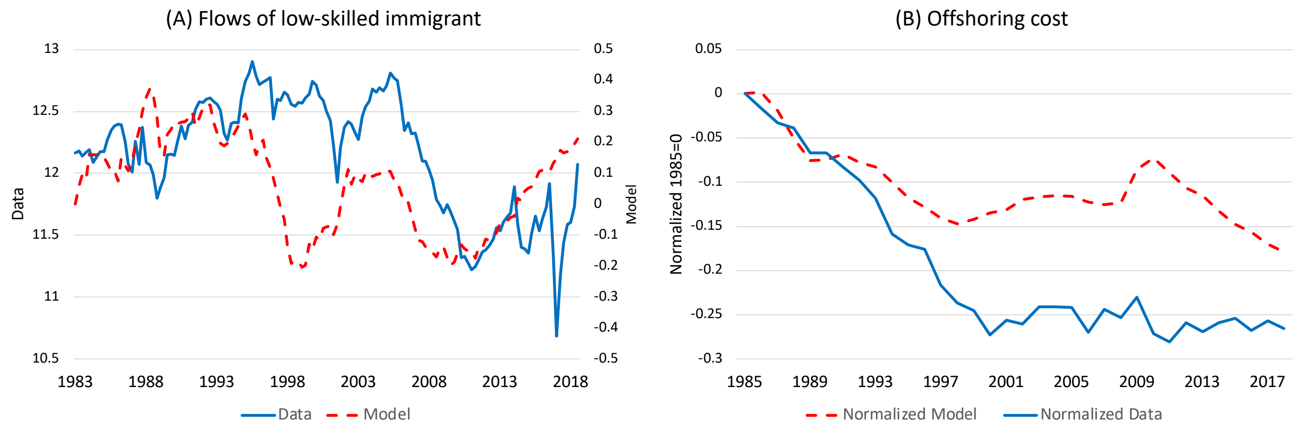
Figure 7(B) shows that the model prediction for the cumulative stochastic innovations affecting the iceberg offshoring cost (dashed line) matches well the trade-weighted ESCAP/World Bank measure of trade costs (solid line). Following the Great Recession, the model predicts an increase in trade costs while the data show a decline after 2007. This apparent discrepancy may be reconciled with additional information not reflected in the trade cost indicator, which fails to account for factors like the increase in trade protectionism during the crisis reflected in the increase in non-tariff barriers (see Georgiadis and Gräb, 2016), and the freeze in trade credit (see Coulibaly et al., 2013).

Taking stock of these findings, the model predictions for the evolution of low-skill immigration and offshoring costs appear largely consistent with the data, which is remarkable given that we do not use data series on labor migration or trade flows in the estimation of the model. Notably, the steady decline in offshoring cost through the end of sample period, both in the data and the model, would exert upward pressure on the skill premium, which is inconsistent with the evidence. As we will show later, the decline in the skill premium is linked to the immigration slowdown after 2007.

[37] See the appendix for details on the smoothing procedure. One-sided estimates of the observed variables deliver a satisfactory in-sample fit. Results are available upon request.

[38] Traditionally, border apprehensions were highly seasonal and peaked in the spring before declining during the hot summer months. These long-lasting patterns vanished after 2013, and apprehensions spiked at different times during the year, which may reflect changes in entry strategies by *coyotes*, or alternatively, the increase in the proportion of migrants crossing the boarder with the intention of surrendering to the authorities and seek refugee status.

**Figure 7:** Flows of low-skill immigrant and offshoring cost predicted by the model




*Note:* This figures show the model predictions for low-skill immigration flows and the iceberg cost offshoring as latent variables as well as their data counterparts, i.e., border apprehensions adjusted for enforcement like in Hanson and Spilimbergo (1999) and Hanson (2006) and constructed trade costs from the ESCAP/World Bank database.

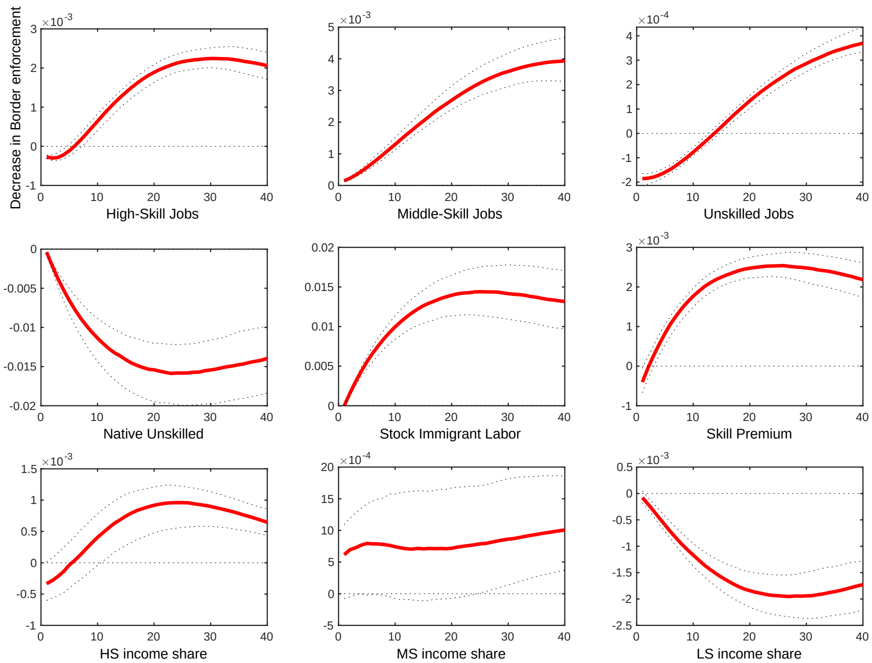
## 5.2 Impulse Response Functions

In this section, we describe the propagation of shocks to a decline in migration, training, and offshoring costs. The Appendix reports a discussion on the effect of technology and demand shocks. We show the estimated median impulse responses (along the 10% and 90% posterior intervals) of key model variables to different stochastic innovations (one standard deviation for each).

**Decline in the sunk migration costs.** Figure 8 shows the response of key variables to a decline in migration costs, which we measure as decline in border enforcement. Immigration inflows rise on impact, but the stock of immigrant labor increases gradually–peaking only after five years (twenty quarters). The inertia in the increase of immigration explain its delayed impact on labor market variables, which is further discussed below for the historical analysis. The native household reacts to higher immigration by investing in training and reallocating labor away from low-skill service occupations and toward high- and middle-skill occupations (consistent with the job task upgrading in Ottaviano et al., 2013). As a result, the fraction of native low-skill jobs declines, while high- and middle-skill jobs rise slowly over time. The downward pressure of higher immigration on low-skill wages – along with the shift in native employment toward high- and middle-skill occupations – leads to an increase in the income shares of high- and middle-skill workers, but to a decline in the income share of low-skill occupations. The skill premium increases as a result. To sum up, low-skill immigration encourages native workers to train and boosts the labor productivity and income for the trained workers.

**Increase in training costs.** Figure 9 shows the impulse responses to an increase in training costs. Due to the higher training costs, more workers choose to remain untrained, boosting the supply of native low-skill labor on impact. This puts downward pressure on associated wages and the price of non-tradable services. Southerners have less incentive to migrate and the stock of immigrants declines gradually over time. This explains the contraction of the *aggregate* supply of low-skill labor at longer horizons despite

**Figure 8:** Impulse response to a decline in migration barriers

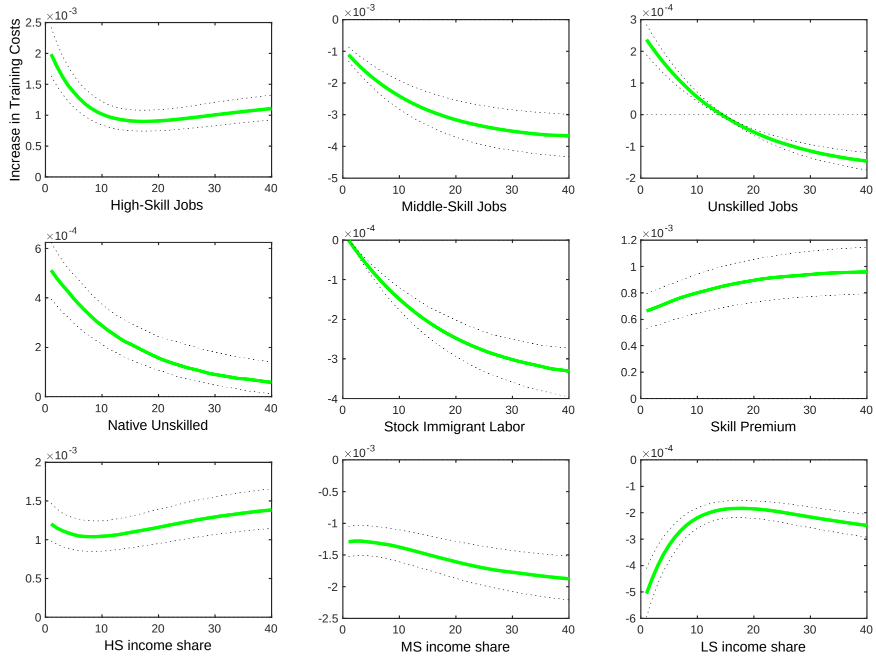



*Note:* This figure illustrates the impulse response of selected variables to the negative shock to immigration costs. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percent posterior.

a lower training choice by natives. In turn, the persistent decrease in training eventually dents labor productivity and further lowers real wages over time, further deterring immigrants to come. A Harrod-Balassa-Samuelson effect takes places, in which lower productivity leads to lower non-tradable prices and, thus, a real exchange rate depreciation. These adjustments explain why, in the margin, there is some increase in high-skill employment. Native skilled workers become more competitive in the global marketplace due to the depreciation in the exchange rate, which allows for some upskilling among the most productive (higher $\mathbf{z}$) middle-skill workers.

**Decline in offshoring costs.** Figure 10 shows the effect of a decline in offshoring costs. Since the effect of the shock is symmetric across countries, we show the impulse responses for Home only. Easier offshoring induces producers to expand the number of tasks executed abroad, which boosts the employment of high-skill workers who execute tasks for the global market, but displaces middle-skilled workers who face lower earnings resulting from the competition of offshore workers. Our result is consistent with the evidence in Oldenski (2014), who shows that middle-skill occupations in routine jobs (e.g., manufacturing) were the most affected by the globalization wave in the past decades. Efficiency gains from task specialization increase, however, which enhances aggregate labor productivity. As aggregate income increases, so does the demand for non-tradable services and low-skill employment, inducing an increase in low-skill immigration from the South (middle panel in the middle row). Thus, the impulse responses

**Figure 9:** Impulse response to an increase in training costs




*Note:* This figure illustrates the impulse response of selected variables to a positive training cost shock. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percent posterior.

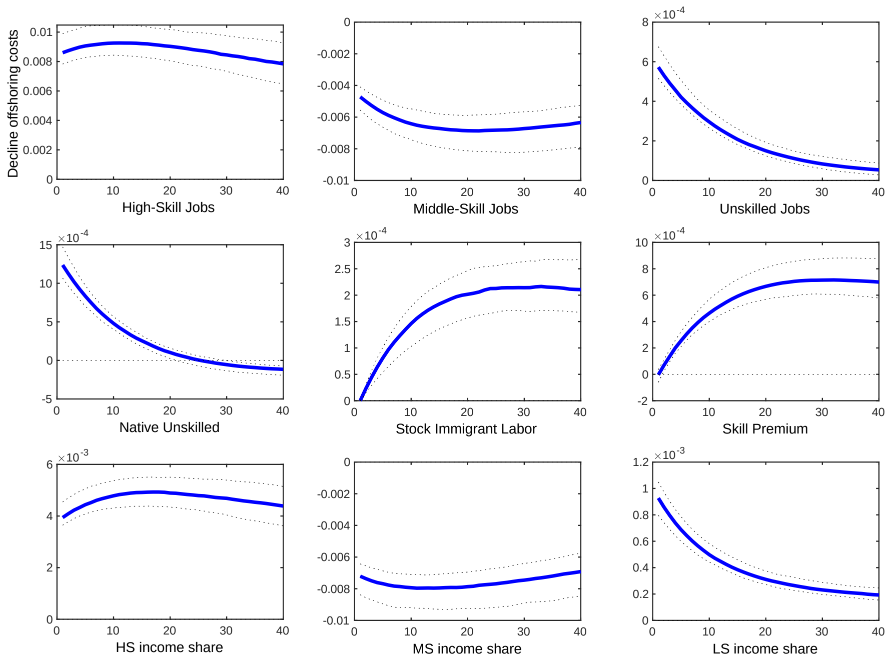
to the decline in offshoring costs are consistent with the evidence for the period 1980-2007 in Figure 1 in the introduction. A deeper integration of the U.S. labor markets into the global economy hollowed out the middle-skill employment while inducing upskilling by natives towards more productive jobs, at the same time with an inflow of low-skill immigrant workers for non-tradable tasks that cannot be executed overseas (the top row). Workers at the upper and lower tails of the skill distribution not only enjoy better employment outcomes but also gain a higher share of income at the expense of those in the middle of the skill distribution ( the bottom row). However, immigration dampens the increase in low-skill wages over time, boosting the skill premium at longer horizons.

## 5.3 Historical Decomposition

Figures 11-16 show the historical contribution of the estimated shocks to key variables in the model for the period 1983:Q2-2018:Q4. The variables include employment and income shares for each skill group, and the labor migration-related indicators, expressed in deviations from balanced-growth (y-axes).

The historical contributions of the distinct shocks to the evolution of each variable are represented by the colored bars. The model predictions for the intensity of U.S./Mexico border enforcement and for training costs reflect the actual data used in the estimation. The observed innovations to U.S. Mexico border enforcement are fully reflected by fluctuations in migration cost shocks, which are exogenous to the model ($\epsilon_t^{fe}$, dark red bars). The same applies to training cost shocks directly taken from the tuition

**Figure 10:** Impulse response to offshoring cost shock



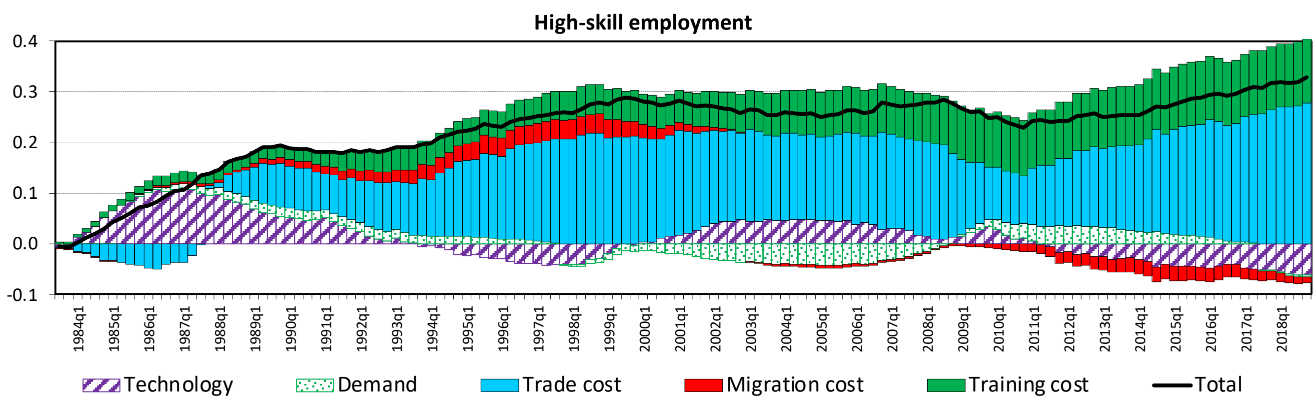

*Note:* This figure illustrates the impulse response of selected variables to the offshoring cost shock. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percent posterior.

data ($\epsilon_t^{Tr}$, solid green bars). Figures A10-A12 in the Appendix display them. The remaining shocks include total factor productivity innovations grouped grouped for all countries (purple), offshoring costs (blue), and demand (white with green dots), which are not directly observed and are backed out with the Kalman filter (see appendix for details).

Overall, the first half of the sample, comprising the period 1983-1996, shows a sustained relaxation in migration barriers associated with the significant increase in migration flows. Swings in border enforcement policy appear to be associated with the U.S. political cycle. The Immigration Reform and Control Act of 1986 provided amnesty for some of the workers who arrived before 1982 but also involved an increase in border enforcement in the late 1980s that was very short-lived, however. The Unauthorized Immigration Reform Act under the Clinton Administration in 1996 was also accompanied by tightened enforcement, which this time showed to be stronger and more persistent. Border enforcement tightened further during the Great Recession building over time the slowdown in immigration. Finally, training costs display a steady upward trend in tuition costs that persists through the sample period used for the estimation.

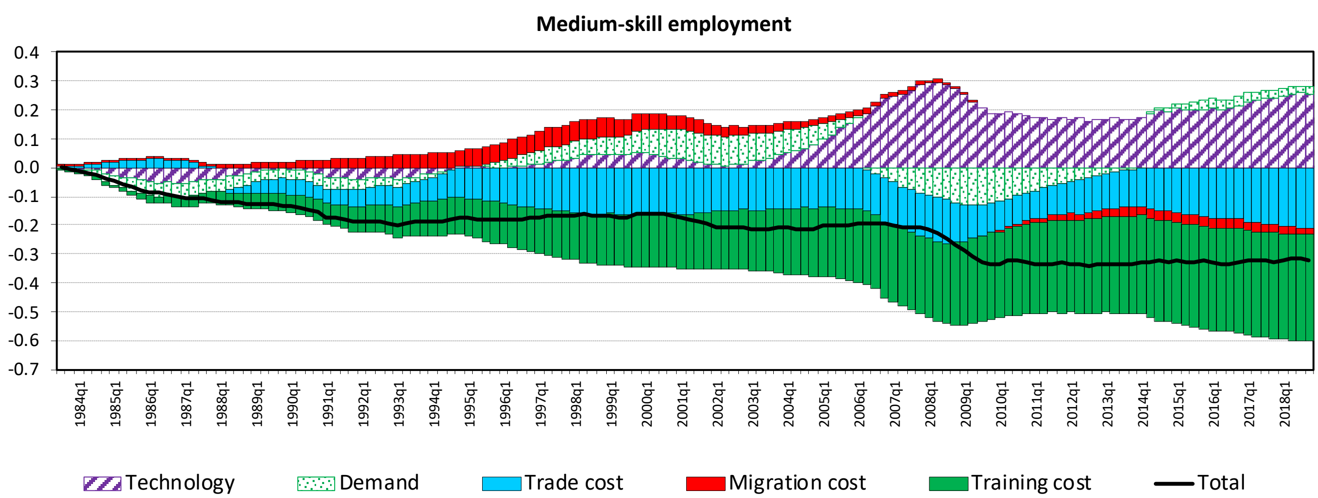
**Accounting for historical events.** The historical decomposition indicates that technological change (dashed-purple bars) played a central role in explaining the increase in inequality among employment skill groups in the 1980s. In comparison, the declining cost of offshoring (light-blue bars) became a dominating factor benefiting employment in high-skill occupations at the expense of middle-skill ones from the 1990s onwards. All this is notably consistent with the microeconomic evidence in Firpo et al. (2011). As shown in Figures 11 and 12, technology shocks lowered middle-skill employment during the three recorded recessions of 1990-91, 2001, and 2007-09, as documented in Jaimovich and Siu (2020). The decrease in migration costs contributed positively to the growth in both high- and middle-skill employment during the late 1980s and the 1990s, as immigration prompted native low-skill workers to undergo training and task upgrading. The increase in real tuition costs during the sample period was detrimental to skill upgrading, however, offsetting some of the increase in skilled labor. Due to the Harrod-Balassa-Samuelson effect explained above, higher tuition costs boosted the international competitiveness of the most productive skilled workers to engage in offshore production.

**Figure 11:** Historical decomposition, high-skilled employment




*Note:* This figure illustrates the historical decomposition of high-skilled employment between 1983 and 2019.

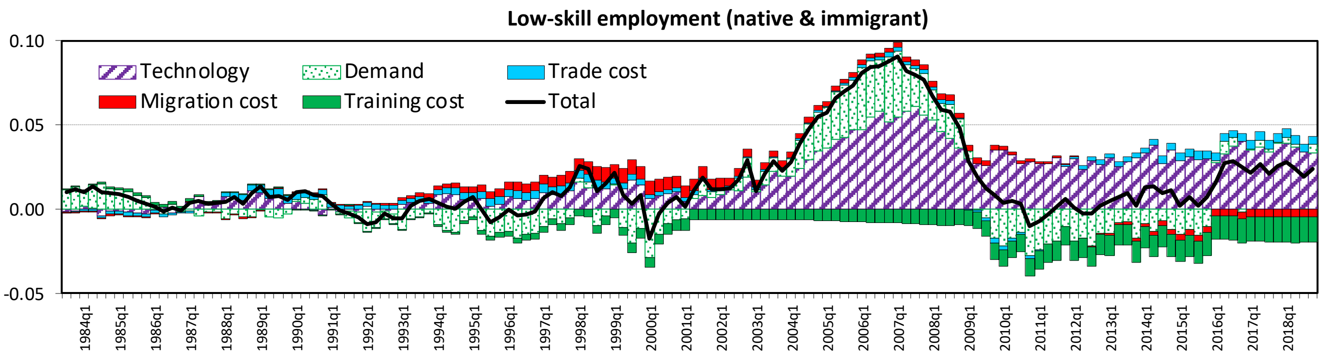
**Figure 12:** Historical decomposition, medium-skilled employment




*Note:* This figure illustrates the historical decomposition of medium-skilled employment between 1983 and 2019.

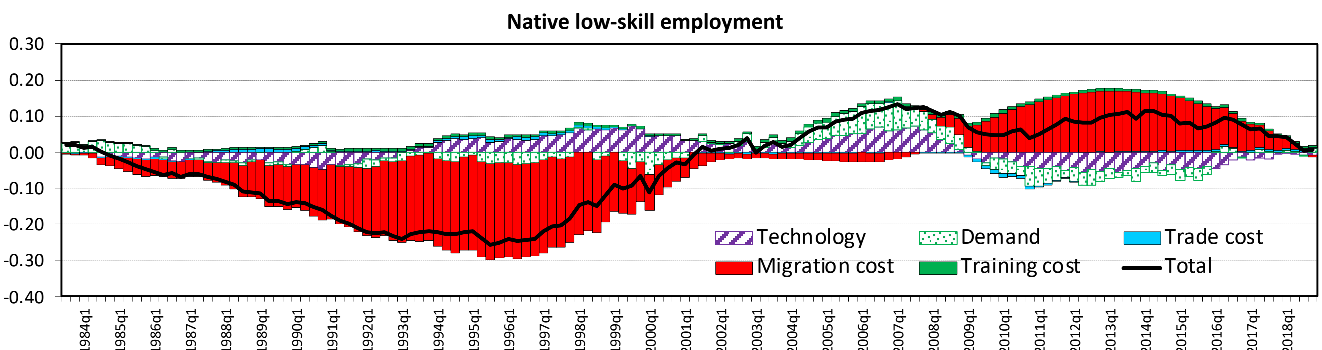
Figure 13 shows the evolution of aggregate low-skill employment, which includes both low-skill immigrants and natives. The decline in offshoring costs and immigration barriers positively contributed to low-skill employment during the first half of the sample period. The relatively contained effect of the decline in immigration costs on the employment of low-skilled workers conceals sizable composition effects between natives and immigrants. As shown in Figures 14 and 15, a remarkable decline in low-skill native employment coincided with a steady increase in immigration inflows in line with the ACS data discussed in the introduction.

**Figure 13:** Historical decomposition, low-skill employment




*Note:* This figure illustrates the historical decomposition of low-skill employment between 1983 and 2019.

**Figure 14:** Historical decomposition, low-skill native employment

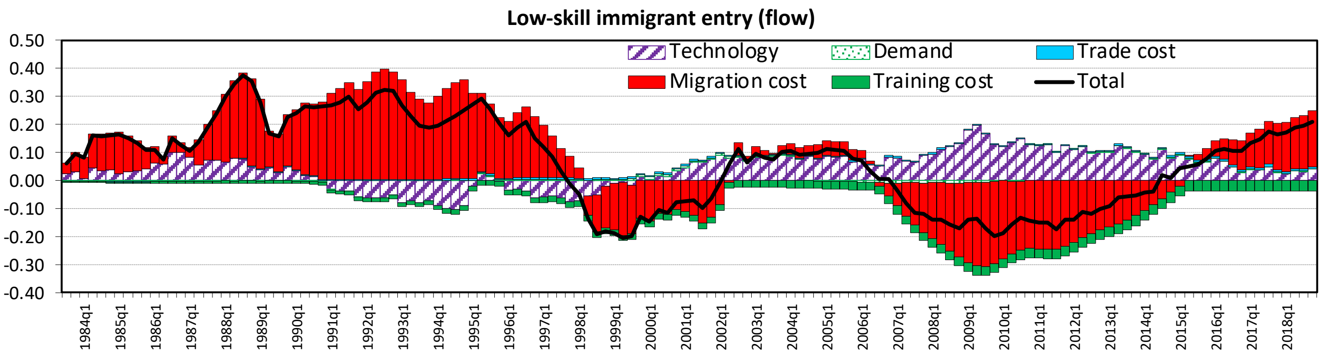



*Note:* This figure illustrates the historical decomposition of employment of low-skill natives between 1983 and 2019.

The positive shocks to productivity and consumption demand (dotted-green bars) that are linked to the housing bubble also contributed to the sizable increase in aggregate low-skill employment in the early 2000s. Conversely, the reversal of these transitory shocks explained the decline in low-skill employment in the aftermath of the Great Recession in 2007. The intuition for the consumption demand shocks, shown in the appendix, is straightforward: the demand shock enhances the demand for both non-tradable and tradable tasks in Home due to their complementary in consumption. As a result, Home relied on Foreign to provide more tradable tasks (leading to an increasing trade deficit) and instead devoted more of its labor to producing non-tradable tasks that couldn't be substituted with imports from Foreign.

In our model, labor markets and trade deficits are tightly interconnected. For instance, in a consumption boom driven by positive demand shocks, the increase in the demand of households is for both tradable goods (e.g., electronics, cars) and non-tradable services (e.g., restaurants) since goods and ser-

**Figure 15:** Historical decomposition, inflow of low-skill immigrants




*Note:* This figure illustrates the historical decomposition of the inflow of low-skill immigrants between 1983 and 2019.

vices are complementary in consumption. The rise in tradable consumption can be satisfied by more imported tasks (boosting the current account deficit), while the increase in demand for non-tradable requires a rise in immigration since those services cannot be offshored. Conversely, negative demand shocks in Foreign may reflect the increase in the supply of foreign savings documented during those years –referred to as the global savings glut– that is not directly accounted by our model.[39] The boom-bust in low-skill (non-tradable) employment during the housing bubble coincided with a sizable increase in the U.S. current account deficit, followed by the remarkable correction after the Great Recession.[40]

Figure 15 shows that the entry of low-skill immigrants was driven by the sustained decline in migration barriers in the 1980s. This policy stance, which was briefly interrupted with the 1986 immigration reform, lasted until the mid-1990s. The 1996 reform initiated a persistent increase in enforcement that turned the migration tide thereafter. This negative trend in immigration was temporarily interrupted with a brief expansion during the housing boom of the early 2000s (which also coincided with a brief relaxation in migration barriers), but resumed at the onset of the Great Recession. Put it differently, once the temporary support to low-skill immigration from the housing boom of the early 2000s subsided, the immigration slump driven by the increase in migration barriers in the late 1990s resumed and persisted until the end of the sample, largely explaining the shortage of low-skill workers motivating our analysis.

Finally, Figure 16 shows the historical decomposition of the wage immigration premium, calculated as the difference between the wages of Southern workers (and low-skilled natives) in Home and those residing in South. Unlike in previous figures, the purple dashed bars groups together demand and productivity shock in Home, while the orange line shows the measured shocks in South. The decrease in immigration barriers in the 1980s delivered a delayed decrease in the immigration wage premium in the 1990s given the inertia previously discussed for Figure 8.[41] Low-skill wages in Home surged temporarily with the housing boom in the mid-2000s and after 2016 when labor markets tightened. The slowdown in immigration initiated in 2006 only had its greatest impact in the 2010s, sustaining wages gains for this skill group despite the tepid labor market recovery in the aftermath of the Great Recession. Such predicted increase in

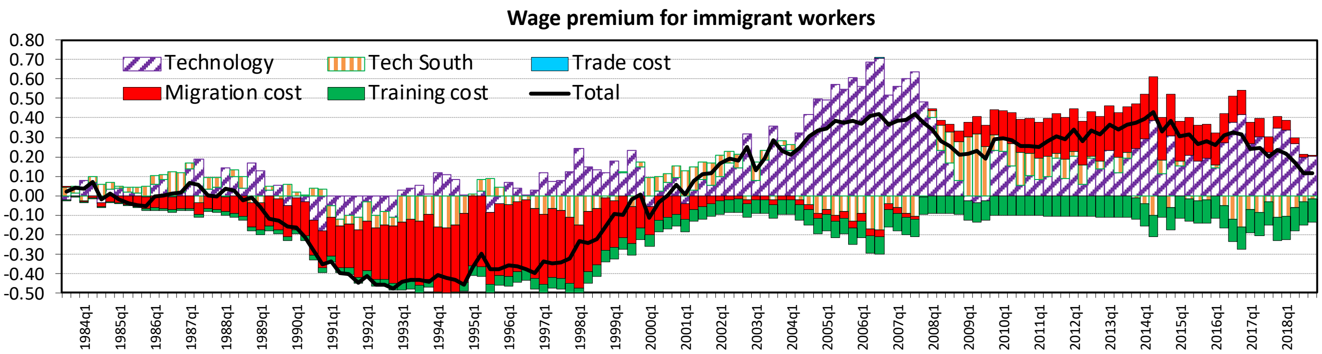
[39]See Kehoe et al. (2018) for a discussion on those forces for macroeconomic performance.

[40]The current account deficit decreased from 6.2% of GDP in 2006:3 to 2.5% in 2009:2.

[41]Such inertia explains why disruptive, but transitory, economic events in Mexico like the 1980's debt crisis, Peso crisis, or the acute contraction in 2009 following the disruption of trade links have limited impact on the wage premium of immigrants.

the immigrant wage premium boosted total low-skill wages and allows the model to match quantitatively the cumulative decline in the U.S. skill premium that coincided with the slowdown in low-skill immigration during the last decade of the sample (5.06 % in the model vs 5.00% in the data).

**Figure 16:** Historical decomposition, wage premium for immigrant workers




*Note:* This figure illustrates the historical decomposition of the wage premium for immigrant workers between 1983 and 2019.

## 6 Welfare Analysis

Using the second-order approximation around the balanced-growth path, we derive welfare gains (losses) as the percent of the expected stream of consumption that one should add (or subtract) that make the representative households as well-off in each counterfactual scenario as in the estimated model, *ceteris paribus*.[42] Our measure of welfare is the present discounted value of the flow of utility.[43] Table 6 shows the welfare outcomes from alternative counterfactual scenarios for immigration and offshoring policies, and alternative trajectories in training costs, which we discuss below.

Rows (1) and (2) in Table 6 show the welfare losses generated by the slowdown in low-skill immigration to Home for households in each economy during 2007-2018. To measure this, we compute welfare differences between a counterfactual scenario in which the average annual growth of low-skilled immigration for the period 2007-2018 would be identical to the one observed during 1983-2006 and the observed one with the immigration slowdown. Row (1) in the table considers the scenario which abstracts from the estimated transitory AR(1) shocks. Results indicate that the representative U.S. native household loses 2.54% of its average consumption in every period as a result of the downshift in immigration from the average growth observed during the 1983-2006 period towards those observed during 2007-2018. Not surprisingly, the losses are much larger in the South (-9.06%), for which immigrant work represent a larger source of income, and tiny for Foreign (-0.19%), which is only marginally affected through indirect channels affecting the real exchange rate.

[42]The approximation is based on the approach developed in Woodford (2003).

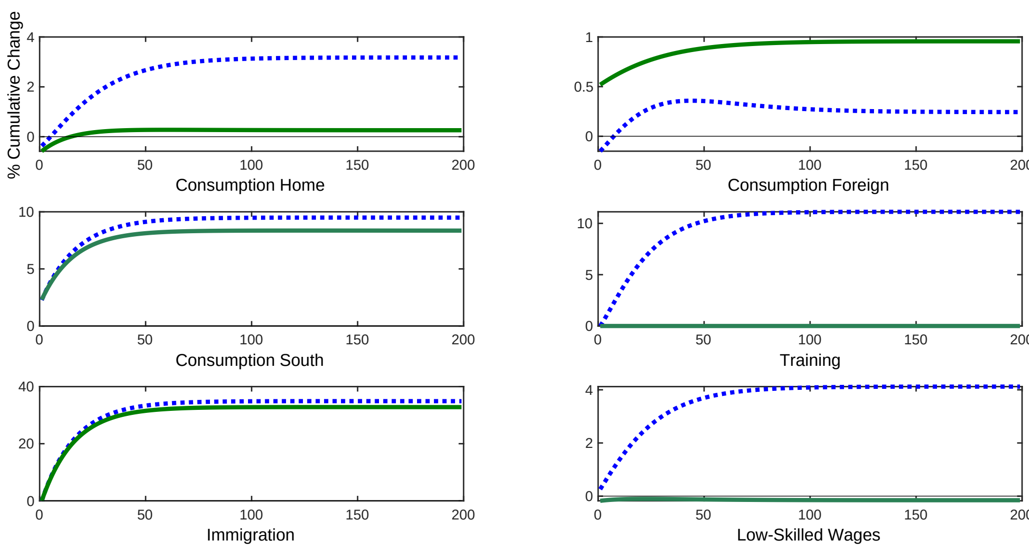
[43]The representative household in Home only accounts for the native workers while the Southern household accounts for the welfare of migrant workers. Implicitly, we assume that migrants in Home use remittances to transfer funds to their country of origin to equalize utility across household members in different locations (see Mandelman and Zlate, 2012, for details). Remittances are netted out in the consolidated current account for Home and South.

**Table 6:** Welfare implications of counterfactual changes in immigration, skill acquisition, and trade

| | Home | Foreign | South |
|---|---|---|---|
| (1) Decline in Immigration | −2.54% | −0.19% | −9.06% |
| (2) Decline in Immigration (with shocks) | −2.52% | −0.29% | −11.00% |
| (3) Decrease in Training Costs | 5.28% | −0.31% | 2.07% |
| (4) Decrease in Training Costs (with shocks) | 5.28% | −0.31% | 2.35% |
| (5) Decrease in Offshoring Costs | 2.99% | 4.19% | 1.30% |
| (6) Decrease in Offshoring Costs (with shocks) | 3.86% | 4.31% | 1.24% |

*Note:* The table shows welfare gains (losses) from three different scenarios—slowdown in immigration, lower training costs, and lower offshoring costs—with or without estimated shocks for each scenario. The gains (losses) are computed relative to alternative scenarios in which low-skill immigration during 2007-2018 would have matched its higher average rate from pre-2007; real tuition costs would have remained at their relatively low levels from 1983; and offshoring costs would have remained at their high levels from 1983, respectively.

**Figure 17:** Welfare analysis: transitional dynamics




*Note:* Blue-dotted line: Immigration returns to pre-2007 trend. Green-Solid: Same case with a fixed-training margin.

To illustrate the mechanism underlying the results, Figure 17 shows that the welfare costs from slower immigration for natives in Home is largely driven by the reduction in training (skill acquisition). This figure illustrates the model dynamics in a scenario in which in the initial period ($t = 1$) the households learn that immigration barriers decline immediately so that, in the new balanced-growth-path, the level of immigration increases, as if the annual growth rate of immigration from 1983-2006 was replicated through 2007-2018.[44] Such a policy change implies that the stock of immigrant labor becomes 35% higher in the new stationary equilibrium compared to the estimated model (blue-dotted line). The green-solid line shows the same counterfactual for immigration, but in this case households cannot optimally increase their training choice in response to lower migration barriers. While the baseline delivers inter-temporal consumption gains of around 3% in the new equilibrium, the inter-temporal gains practically disappear

[44]To avoid explosive growth paths we assume that the immigrant to native labor force fully stabilizes after 2018.

with a fixed training choice.[45] If households cannot invest in training the gains from immigration are practically muted, with the potential gains from lower consumer price for non-tradables being largely offset by lower wages for the low-skilled natives. A central result of our analysis is that the native workers' decision to invest in skills can deliver sizeable gains from low-skill immigration even under the extreme assumption of perfect substitutability between low-skill native and immigrant labor (and no capital accumulation). Allowing for some degree of complementarity in production between natives and immigrants would deliver even larger gains from immigration.[46]

Row (2) in Table 6 includes the estimated transitory shocks to the analysis. The inclusion of shocks allows us to account for the welfare effects of transitory innovations perturbing the model dynamics along balanced growth under different policy scenarios. The results are different from those in row (1), since the model is approximated to a second order and entails non-linearities. Thus, the welfare losses from lower migration for the South are significantly higher (11%) in the presence of shocks. This finding highlights the role of labor migration as a possible insurance mechanism for the Southern household. For instance, if the South is hit by a negative shock (e.g., the 1994 Mexican Peso crisis), earnings are much lower for those residing in the South but not for the immigrants working in Home who can support their families back at home. Consistent with our model, empirical evidence shows that migrants send more remittances in times of distress to support consumption in their native countries. For Home, instead, the losses are practically the same with or without shocks, which is due to high immigration barriers causing a lock-in effect whereby the stock of established immigrants responds slowly to shocks. For instance, migrants do not return to South during a recession in Home, as they have to pay a hefty sunk migration cost to re-enter after the Home economy recovers. Similarly, immigrants would be slow to arrive if there is a increase in consumer demand in Home which is only transient in nature (as we will discuss in the next section).

Rows (3) and (4) in Table 6 show the counterfactuals with real training costs remaining at the 1983 values.[47] As expected, the benefits are sizable for the Home economy, whose consumption stream rises by 5.28% due to increases in labor productivity. More training by Home natives is also beneficial for the South, as the need to fulfill low-skill tasks through enhanced immigration is greater. The effect on Foreign welfare is negligible. On one hand, Foreign benefits from a greater variety of labor tasks provided by a relatively more skilled labor force in Home. On the other hand, more tasks from Home also causes some displacement of skilled workers in Foreign. The results are essentially identical when we include transitory shocks, as the training choice involves a costly irreversible sunk cost and is unlikely to be affected by transitory shocks.

Rows (5) and (6) in Table 6 account for the potential welfare gains derived from the decrease in trade/offshoring costs observed during the sample period. The reduction in the iceberg offshoring costs in Home is welfare-improving for all the three economies. Home becomes specialized in its most productive labor tasks while Foreign benefits from the increasing availability of complementary Home tasks, which

[45] The 2.54% gains mentioned above are computed as stable stream (i.e., like an annuity). In reality, consumption increases slowly as training boost labor productivity over time.

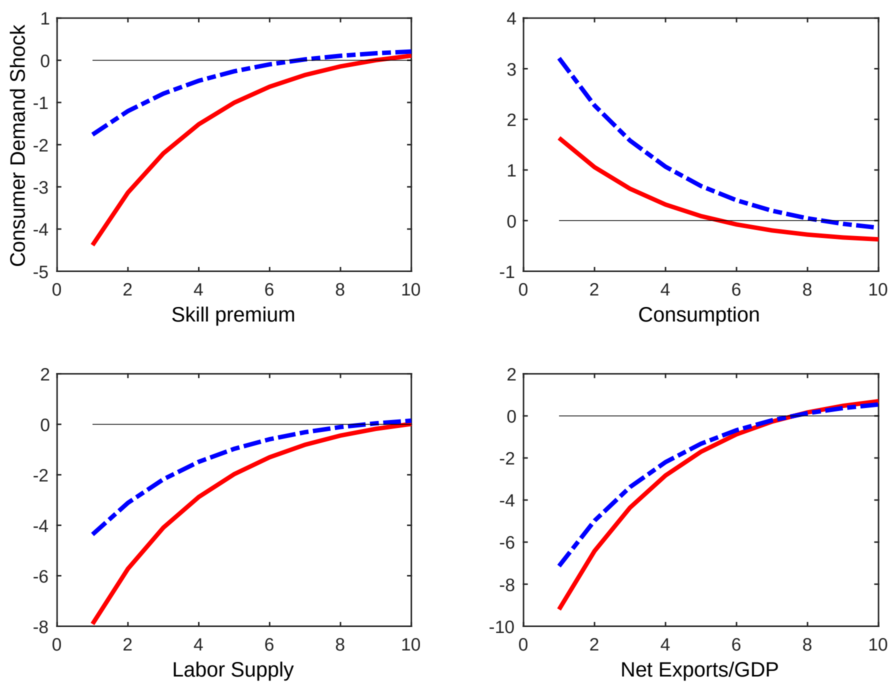
[46] Results are available upon request.

[47] Real tuition and other school fees tripled during the sample period used in the estimation (1983-2018).

also enhances task specialization. The price (wage) impact on the terms-of-trade (labor) resulting from increasing availability of Home tasks in Foreign explains why the gains are relatively larger for Foreign. In addition, some of the Home's welfare gains are transferred to South through the income of immigrant workers. Importantly, comparing row (5) to row (6), economies more open to trade/offshoring are also better hedged from domestic shocks. While Kim and Kim (2003) shows that international bond trading helps to hedge minor and highly transitory shocks, our results indicate that trade and offshoring enhances the scope of risk-sharing in face of multiple highly persistent shocks (some close to be near-root).

**COVID-19 policy responses: the CARES Act and labor shortages.** We finally apply the estimated model to study the impact of labor shortages during the COVID-19 pandemic.[48] One notable development amid the labor shortages consequent to the COVID-19 pandemic was the unprecedented fiscal stimulus payments under the CARES Act enacted in March 2020. The stimulus bill unleashed approximately 5 trillion dollars (about 25 percent of GDP at the onset of the crisis) in direct transfers (see U.S. Treasury Report 2022), which was accompanied by a large-scale monetary policy easing by the Federal Reserve. On the supply side, the COVID-19 pandemic significantly restrained mobility of the labor force.

**Figure 18:** COVID-19 simulation: IRF to the CARES demand shock



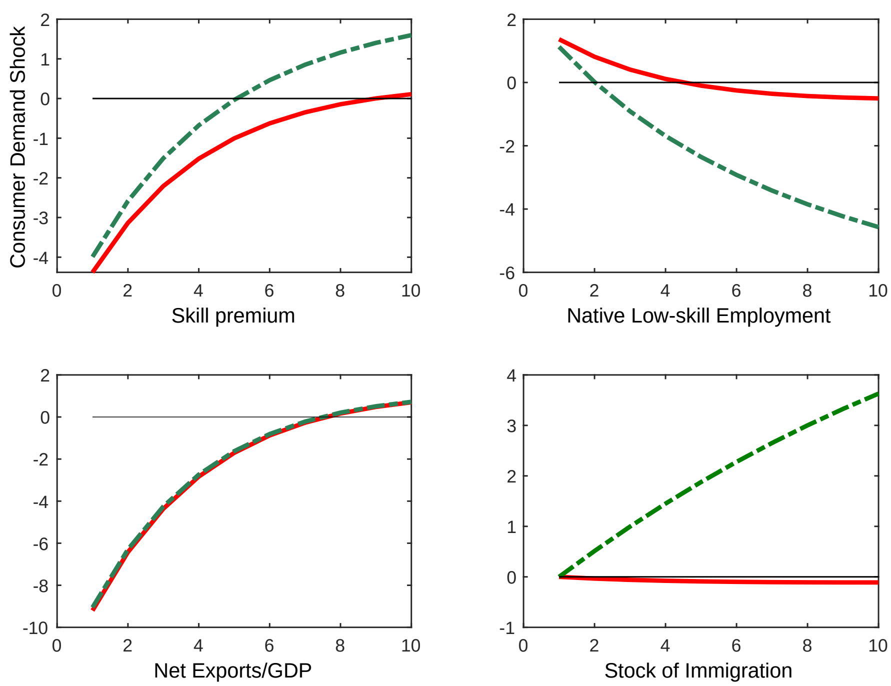

*Note:* Blue-dotted line: CARES demand shock, Red-solid line: Same scenario with negative shock to labor supply.

While our stylized model cannot accommodate interventions in fiscal and monetary policy, we can

[48] The shock processes estimated for the period (1983-2018) and used in welfare computations rules out the possibility of a shock of the magnitude of the COVID-19 pandemic.

approximate them using a large positive shock to consumer demand (i.e., a negative shock to the discount rate), as standard in the macro literature.[49] The blue-dotted line in Figure 18 illustrates the case with the positive demand shock and constrained labor supply. A demand shock boosts the demand for consumption but also for leisure, leading to a decline in the aggregate labor supply. The model's implication is consistent with a phenomenon popularly known as the *Great Resignation* that took place amid generous transfers from the government.[50] The boost to consumption was mostly fulfilled by an increase in imported goods, evinced by a sharp decline in the net exports to GDP ratio. The COVID-19 recession was atypical in that it was associated with a notable increase in the trade deficit (from 2.5 percent to 5 percent of GDP) rather than the current account reversal typically linked with economic downturns. The supply of low-skill services was, however, greatly constrained by pervasive shortages of low-skill immigrant labor. Therefore, the positive demand shock increases the price of the non-tradable services and the wages of low-skill workers producing these services. Low-skill immigration does not respond significantly to the higher low-skill wages in Home, however, given the transitory nature of this shock. As a result, the change in the entry of immigrants is limited.

**Figure 19:** COVID-19 simulation: The impact of an increase in immigration




*Note:* Red-solid line: see Figure 18, Green-dotted line: Same scenario with a policy-induced increase in immigration.

[49]We must generate a sizable decline in the discount rate to match the large jump in household consumption observed following successive rounds of fiscal stimulus. To make the simulation relevant for our context, we suppress the skill acquisition channel in this counterfactual scenario. Without this assumption, households would borrow against their future income to invest heavily in training, which would be counterfactual. See Ikeda et al. (2023) for an application with large shocks to consumer demand achieved with shocks to the discount factor.

[50]Evidence suggests that overly generous stimulus payments and unemployment benefits triggered an increase in voluntary separations, see Arbogast and Dupor (2022).

The sluggish recovery in the labor force in the aftermath of the COVID-19 pandemic cannot be solely explained by a higher preference for leisure. Mobility restrictions and fear of contagion of the disease, as new variants of the COVID-19 virus emerged, also had a substantial adverse impact on labor force participation. The fall in participation was particularly acute in the case of low-skill service occupations that require physical contact with consumers and cannot be offshored or performed with remote working (i.e., via telecommunication). The red-solid line in Figure 18 illustrates a scenario in which we simulate a negative labor supply shock to match the observed decrease in the participation rate at the time the stimulus payments. The restricted labor participation, combined with a positive demand shock, generates a spike in low-skill wages and the price of low-skill services, a larger drop in the skill premium, which closely matches the quantitative evidence shown in the introduction–See Figure 2(A)– along with a smaller increase in consumption.

From a normative perspective, a potential policy solution for an acute shortage of low-skill labor is to relax immigration policy and encourage low-skill immigration. Figure 19 replicates the previous scenario (positive demand shock with restricted labor supply) along with a counterfactual increase in low-skill immigrant inflows (i.e., calibrated after the spike in apprehensions during 2021-2022). The red-solid line is the same as the red curve in Figure 18. The green-dotted line shows the counterfactual case in which immigration barriers are relaxed. The increase in low-skill immigration makes little difference on impact for the skill premium and low-skill native employment given its inertia. Despite the relaxation of immigration policy, it takes several years of robust increase in immigration flows for the stock of low-skill immigrant workers to be makeup for shortages. In our simulation, the temporary consumer demand shock already dissipates by the time that the stock of immigrant labor increases sufficiently.

# 7 Conclusion

We use regional U.S. Census data from the American Community Survey to establish several new facts related to the sustained decline in immigration and the severe shortage of low-skill labor that began with the Great Recession of 2007 in the United States. We show that the slowdown in low-skill immigration resulted in higher low-skill wages and a fall in the skill premium that overturned its four-decade-long upward trend. In turn, the lower skill premium coincided with a reduction in educational attainment by the native population and a decline in the real costs of education. We use our new regional evidence and aggregate patterns to develop a novel stochastic growth model with endogenous immigration, training, and offshoring choices. The estimated model implies that the slowdown in low-skill immigration resulted in a shortage of low-skilled workers, which in turn boosted low-skill wages that can explain the observed decline in the skill-premium. The lower skill premium reduces the natives' incentive to train in the model.

The estimated structural model allows us to study the welfare effects of the slowdown in immigration and the unprecedented decline in the skill premium. Immigrants work in non-tradable services that cannot be offshored, so labor shortages translate directly into higher consumer prices when demand increases. In fact, when we applied our model to study the effects of policy stimulus through the CARES Act in response to the COVID-19 pandemic, we found that acute shortages of low-skilled immigrant labor caused a spike in consumer prices that significantly eroded the benefit of the policy stimulus. That said, in the quantitative analysis, diminishing returns to education that discourage skill acquisition constitute the most detrimental welfare impact of slow immigration on natives, as they reduce labor productivity over time.

Our study suggests several fruitful explorations on the interaction between immigration and macroeconomic performance. Since our focus is primarily on the interplay between low-skill migration, the skill premium, and labor market outcomes, we have abstracted from significant changes in the demographic structure of the workforce. Extending the analysis to study the effect of a reduction in labor force participating arising from population ageing would be an important extension for future research. Similarly, the demographic shift toward lower fertility rates in Latin America that began in the 1980s may also have changed the dynamics of low-skill immigration, with important ramifications for the U.S. economy. Finally, the slowdown in low-skill immigration documented in our study was abruptly reversed in the end of 2021, with immigration having recovered since then. Yet, the origin and characteristics of immigrant workers have changed, with Mexico and Central America having declined in prominence as suppliers of immigrant workers to the United States in the last five years. The implications of those changes are unclear, but they will certainly play an important role for the labor market dynamics and living standards in time to come. We plan to study some of these issues in future research.

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# Slowdown on Immigration, Labor Shortages, and Declining Skill Premia.

**TECHNICAL APPENDIX**

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This section presents additional materials and results. It includes:

1. The system equations characterizing the equilibrium conditions of the model, where real variables are re-scaled to account for the unit-root technology process.
2. Data sources and Bayesian estimation: description of the data sources, the estimation methodology, and the Kalman smoothing procedure.
3. Additional estimation results for the baseline model: the prior and posterior densities of model parameters, Markov Chain Monte Carlo (MCMC) multivariate convergence diagnostics, impulse responses and variance decomposition.

[1]The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Federal Reserve Banks of Atlanta, The Board of Governors or the Federal Reserve System.

# 1 Normalized Model Equations

The presence of a unit-root global technology shock makes the model non-stationary. Therefore, some of the real variables–i.e., mostly those expressing quantities such as output, consumption, and bond holdings–are re-scaled by the world productivity $\mathbb{X}_t$ to become stationary. In the equations below, the variables marked with hats are subject to such a normalization. For instance, the normalized total value added in Home is $\hat{Y}_t = \frac{Y_t}{\mathbb{X}_t}$. A similar normalization holds for the remaining variables in Home, Foreign, and the South. Notice that employment and prices are stationary, so they are not re-scaled. In what follows, we provide the equations for Home and South. For Foreign, the equations and variables are similar to those in Home, except that there is no immigration from South into Foreign. Variables for Foreign and South are marked with an asterisk and a $s$ superscript, respectively.

**Equations for Home** The average real wages in the middle-skill and high-skill occupations:

$$\tilde{w}_{D,t} = w_{D,t}(\tilde{\mathbf{z}}_{D,t},.) = \frac{\theta}{\theta-1}\frac{\hat{w}_{\mathbf{u},t}}{\varepsilon_t^z v}, \text{ where } v = \left[\frac{k}{k-(\theta-1)}\right]^{\frac{1}{(\theta-1)}} \tag{A1}$$

$$\tilde{w}_{X,t} = w_{X,t}(\tilde{\mathbf{z}}_{X,t},.) = \frac{1}{\mathbb{Q}_t}\left(\tau\varepsilon_t^{\tau}\right)\frac{\theta}{\theta-1}\frac{\hat{w}_{\mathbf{u},t}}{\varepsilon_t^z \tilde{\mathbf{z}}_{X,t}} \tag{A2}$$

The average skill income premia for the tasks executed and delivered domestically ($\hat{\pi}_{D,t}$, which includes both middle-skill and high-skill occupations) and for tasks executed domestically and delivered to Foreign ($\widetilde{\pi}_{X,t}$, which includes only high-skill occupations):

$$\widetilde{\pi}_{D,t} = \hat{\pi}_{D,t}(\tilde{\mathbf{z}}_{D,t},.) = \frac{1}{\theta}\left(\tilde{w}_{D,t}\right)^{1-\theta}\hat{\mathbb{N}}_t \tag{A3}$$

$$\widetilde{\pi}_{X,t} = \hat{\pi}_{X,t}(\tilde{\mathbf{z}}_{X,t},.) = \mathbb{Q}_t\frac{1}{\theta}\left(\tilde{w}_{X,t}\right)^{1-\theta}\hat{\mathbb{N}}_t^* - \hat{f}_{o,t} \tag{A4}$$

where $\hat{f}_{o,t} = \frac{\hat{w}_{\mathbf{u},t} f_o}{\varepsilon_t^z}$ is the fixed cost of offshoring, and $\hat{\mathbb{N}}_t$ and $\hat{\mathbb{N}}_t^*$ are the demand for the composite of tradable tasks in Home and Foreign.

The average skill income premium in middle-skill and high-skill occupations:

$$\widetilde{\pi}_t = \frac{\left(N_{D,t}\widetilde{\pi}_{D,t} + N_{X,t}\widetilde{\pi}_{X,t}\right)}{N_{D,t}} \tag{A5}$$

The wage bill:

$$\mathbb{W}_t = \left[N_{D,t}\left(\tilde{w}_{D,t}\right)^{1-\theta} + N_{X,t}^*\left(\tilde{w}_{X,t}^*\right)^{1-\theta}\right]^{\frac{1}{1-\theta}}, \text{ where } \mathbb{W}_t \equiv 1 \text{ is set as the numeraire.} \tag{A6}$$

The sunk training cost in units of the numeraire:

$$\hat{f}_{j,t} = \frac{\hat{w}_{\mathbf{u},t}\left(f_j \varepsilon_t^{Tr}\right)^{\Theta_{fj}}}{\varepsilon_t^z} \tag{A7}$$

The share of offshoring occupations and the offshoring equilibrium condition:

$$\frac{N_{X,t}}{N_{D,t}} = \left(\frac{1}{\tilde{\mathbf{z}}_{X,t}}\right)^k v^k \tag{A8}$$

$$\widetilde{\pi}_{X,t} = \hat{f}_{o,t}\frac{\theta-1}{k-(\theta-1)} \tag{A9}$$

where the average productivity in high-skill occupations $\tilde{\mathbf{z}}_{X,t} = \mathbf{z}_{X,t} v$ is a function of the offshoring productivity cutoff $\mathbf{z}_{X,t}$.

The law of motion for the number of trained occupations (job turnover):

$$N_{D,t} = (1-\delta)(N_{D,t-1} + N_{E,t-1}) \tag{A10}$$

Household optimality conditions (i.e., marginal utility of consumption, labor supply, training decision, and the Euler equation for bonds):

$$\hat{\zeta}_t = \frac{\varepsilon_t^b \left(\hat{C}_t\right)^{-\gamma}}{P_t}, \text{ where } \hat{\zeta}_t = \zeta_t (\mathbb{X}_t)^{\gamma} \tag{A11}$$

$$a_n \left(L_t\right)^{\gamma_n} \left(\hat{C}_t\right)^{\gamma} = \frac{\hat{w}_{\mathbf{u},t}}{P_t} \tag{A12}$$

$$\hat{f}_{j,t} = \beta \left(1-\delta\right) \mathbb{E}_t \left[ \frac{\hat{\zeta}_{t+1}}{\hat{\zeta}_t} (\hat{f}_{j,t+1} + \tilde{\pi}_{t+1}) \left(\frac{\mathbb{X}_{t+1}}{\mathbb{X}_t}\right)^{1-\gamma} \right] \tag{A13}$$

$$q_t = \beta \mathbb{E}_t \left[ \left(\frac{\mathbb{X}_{t+1}}{\mathbb{X}_t}\right)^{-\gamma} \frac{\hat{\zeta}_{t+1}}{\hat{\zeta}_t} \right] - \phi \hat{B}_t \tag{A14}$$

Uncovered interest rate parity condition:

$$\mathbb{E}_t \left[ \frac{\hat{\zeta}^*_{t+1}}{\hat{\zeta}^*_t} \left(\frac{\mathbb{X}_{t+1}}{\mathbb{X}_t}\right)^{-\gamma} \frac{\mathbb{Q}_t}{\mathbb{Q}_{t+1}} \right] = \mathbb{E}_t \left[ \frac{\hat{\zeta}_{t+1}}{\hat{\zeta}_t} \left(\frac{\mathbb{X}_{t+1}}{\mathbb{X}_t}\right)^{-\gamma} \right] - \phi \frac{\hat{B}_t}{\beta} \tag{A14a}$$

Aggregate accounting and current account:

$$q_t \hat{B}_t = \left(\frac{\mathbb{X}_{t-1}}{\mathbb{X}_t}\right) \hat{B}_{t-1} + \hat{w}_{\mathbf{u},t} L_t + N_{D,t} \tilde{\pi}_t - P_t \hat{C}_t - \hat{f}_{e,t} N_{E,t} - \frac{\phi}{2} \hat{B}_t^2 \tag{A15}$$

$$q_t \hat{B}_t = \left(\frac{\mathbb{X}_{t-1}}{\mathbb{X}_t}\right) \hat{B}_{t-1} + \mathbb{Q}_t N_{X,t} \left(\tilde{w}_{X,t}\right)^{1-\theta} \hat{\mathbb{N}}^*_t - N^*_{X,t} \left(\tilde{w}^*_{X,t}\right)^{1-\theta} \hat{\mathbb{N}}_t - \frac{\phi}{2} \hat{B}_t^2 \tag{A16}$$

Income-based GDP in units of the consumption good:

$$\hat{Y}_t = \frac{\left(N_{D,t} \tilde{\pi}_t + \hat{w}_{\mathbf{u},t} L_t + \hat{w}_{\mathbf{i},t} L^s_{\mathbf{i},t}\right)}{P_t}. \tag{A17}$$

The production for the traded aggregate and the non-traded goods, as well as the relative demand for low-skill native and immigrant labor:

$$\hat{Y}_{T,t} = \hat{\mathbb{N}}_t \tag{A18}$$

$$\hat{Y}_{N,t} = L^A_{N,t} = \left[ \alpha \left(L_{N,t}\right)^{\frac{\sigma_N - 1}{\sigma_N}} + (1-\alpha) \left(L^s_{\mathbf{i},t}\right)^{\frac{\sigma_N - 1}{\sigma_N}} \right]^{\frac{\sigma_N}{\sigma_N - 1}} \tag{A19}$$

$$\frac{\hat{w}_{\mathbf{u},t}}{P_{N,t}} = \alpha \left(\frac{L_{N,t}}{\hat{Y}_{N,t}}\right)^{-\frac{1}{\sigma_N}} \tag{A20}$$

$$\frac{\hat{w}_{\mathbf{i},t}}{P_{N,t}} = (1-\alpha) \left(\frac{L^s_{\mathbf{i},t}}{\hat{Y}_{N,t}}\right)^{-\frac{1}{\sigma_N}} \tag{A21}$$

Since there is no immigration into Foreign, $\hat{Y}^*_{N,t} = L^*_{N,t}$ and $P^*_{N,t} = \hat{w}^*_{\mathbf{u},t}$.

The CPI index, consumption basket, and relative demand:

$$P_t = \left[ \gamma_c \left(P_{T,t}\right)^{1-\rho_c} + (1-\gamma_c) \left(P_{N,t}\right)^{1-\rho_c} \right]^{\frac{1}{1-\rho_c}}, \text{ where } P_{T,t} = \mathbb{W}_t \equiv 1 \text{ is the numeraire.} \tag{A22}$$

$$\hat{C}_t = \left[ \gamma_c^{\frac{1}{\rho_c}} \left(\hat{C}_{T,t}\right)^{\frac{\rho_c - 1}{\rho_c}} + (1-\gamma_c)^{\frac{1}{\rho_c}} \left(\hat{Y}_{N,t}\right)^{\frac{\rho_c - 1}{\rho_c}} \right]^{\frac{\rho_c}{\rho_c - 1}} \tag{A23}$$

$$\frac{\hat{C}_{T,t}}{\hat{Y}_{N,t}} = \frac{\gamma_c}{1-\gamma_c} \left(\frac{1}{P_{N,t}}\right)^{-\rho_c} \tag{A24}$$

**Equations for the Southern economy** Free entry condition and the sunk emigration cost:

$$\hat{f}_{e,t} = \frac{\hat{w}_{\mathbf{i},t}\left(f_e \varepsilon_t^{f_e}\right)}{\varepsilon_t^z} \tag{A25}$$

Law of motion of the stock of immigrant labor:

$$L^s_{\mathbf{i},t} = (1-\delta_l)(L^s_{\mathbf{i},t-1} + L^s_{\mathbf{e},t}) \tag{A26}$$

Household budget constraint:

$$\hat{w}_{\mathbf{i},t} L^s_{\mathbf{i},t} + \hat{w}^s_{\mathbf{u},t}\left(L^s_{\mathbf{u},t} - L^s_{\mathbf{i},t}\right) = \hat{f}_{e,t} L^s_{\mathbf{e},t} + P^s_t \hat{C}^s_t, \tag{A27}$$

Household optimality conditions (i.e., marginal utility of consumption, labor supply, and the emigration decision) :

$$\hat{\zeta}^s_t = \frac{\left(\hat{C}^s_t\right)^{-\gamma}}{P^s_t}, \text{ where } \hat{\zeta}^s_t = \zeta^s_t(\mathbb{X})^{\gamma} \tag{A28}$$

$$a^s_n \left(L^s_{\mathbf{u},t}\right)^{\gamma^s_n} (\hat{C}^s_t)^{\gamma} = \frac{\hat{w}^s_{\mathbf{u},t}}{P^s_t} \tag{A29}$$

$$\hat{f}_{e,t} = \beta\,(1-\delta)\,\mathbb{E}_t\left[\frac{\hat{\zeta}^s_{t+1}}{\hat{\zeta}^s_t}\left(\hat{f}_{e,t+1} + (\hat{w}_{\mathbf{i},t+1} - \hat{w}^s_{\mathbf{u},t+1})\right)\left(\frac{\mathbb{X}_{t+1}}{\mathbb{X}_t}\right)^{1-\gamma}\right] \tag{A30}$$

Production of the non-traded good:

$$\hat{C}^s_{N,t} = \varepsilon^s_t\left(L^s_{\mathbf{u},t} - L^s_{\mathbf{i},t}\right) \tag{A31}$$

$$P^s_t = \frac{\hat{w}^s_{\mathbf{u},t}}{\varepsilon^s_t} \tag{A32}$$

Consumption of the traded aggregate good from Home:

$$\hat{C}^s_{T,t} = \hat{Y}_{T,t} - \hat{C}_{T,t}$$

Aggregate consumption:

$$\hat{C}^s_t = \left[(\gamma^s_c)^{\frac{1}{\rho^s_c}}\left(\hat{C}^s_{T,t}\right)^{\frac{\rho^s_c-1}{\rho_c}} + (1-\gamma^s_c)^{\frac{1}{\rho^s_c}}\left(\hat{C}^s_{N,t}\right)^{\frac{\rho^s_c-1}{\rho_c}}\right]^{\frac{\rho^s_c}{\rho^s_c-1}} \tag{A33}$$

$$P^s_t = \left[\gamma^s_c + (1-\gamma^s_c)\left(P^s_{N,t}\right)^{1-\rho^s_c}\right]^{\frac{1}{1-\rho^s_c}}, \text{ since } P_{T,t} \equiv 1 \tag{A34}$$

$$\frac{\hat{C}^s_{T,t}}{\hat{C}^s_{N,t}} = \frac{\gamma^s_c}{1-\gamma^s_c}\left(\frac{1}{P^s_{N,t}}\right)^{-\rho^s_c} \tag{A35}$$

**Employment and income shares by skill group in Home** The number of high-skill occupations is $N_{X,t}$; the number of middle-skill occupations is $N_{M,t} = N_{D,t} - N_{X,t}$. Aggregate hours for low-skill employment (natives and immigrants) is:

$$L^{Aggr}_{N,t} = L_{N,t} + L^s_{\mathbf{i},t} \tag{A36}$$

Income share of high-skill labor:

$$Share_{H,t} = \frac{N_{X,t}(\widetilde{\pi}_{X,t} + \widetilde{\pi}_{DX,t}) + L_t^{\tilde{\mathbf{z}}_{X,t}}\hat{w}_{\mathbf{u},t}}{\hat{Y}^{\mathbb{W}}_t}, \tag{A37}$$

where $\widetilde{\pi}_{X,t}$ (defined above) is the skill income premium for tasks executed in high-skill occupations that are actually offshored; $\widetilde{\pi}_{DX,t}$ is the skill income premium for the tasks executed in high-skill occupations that are suitable to be offshored (i.e. with productivity above the threshold value $\mathbf{z}_{X,t}$) but are executed for the domestic market; $L_t^{\tilde{\mathbf{z}}_{X,t}}$ is the total units of raw labor embodied in tasks executed in high-skill occupations and sold to Foreign; and $Y_t^{\mathbb{W}}$ is the income-based GDP net of training costs expressed in terms of the numeraire. All these are defined below:

$$\widetilde{\pi}_{DX,t} = \frac{1}{\theta}\left(\frac{\theta}{\theta-1}\frac{\hat{w}_{\mathbf{u},t}}{\varepsilon_t^z \tilde{\mathbf{z}}_{X,t}}\right)^{1-\theta}\hat{\mathbb{N}}_t \tag{A38}$$

$$L_t^{\tilde{\mathbf{z}}_{X,t}} = N_{X,t}\left[(\theta-1)\frac{\widetilde{\pi}_{DX,t}}{\hat{w}_{\mathbf{u},t}} + (\theta-1)\left(\frac{\widetilde{\pi}_{X,t}}{\hat{w}_{\mathbf{u},t}} + \frac{f_o}{\varepsilon_t^z}\right) + \frac{f_o}{\varepsilon_t^z}\right] \tag{A39}$$

$$\hat{Y}_t^{\mathbb{W}} = P_t\hat{Y}_t - \hat{f}_{j,t}N_{E,t} \tag{A40}$$

Income share for the low-skill labor input, including both natives and immigrants:

$$Share_{L,t} = \frac{\hat{w}_{\mathbf{u},t}L_{N,t} + \hat{w}_{\mathbf{i},t}L_{\mathbf{i},t}^s}{\hat{Y}_t^{\mathbb{W}}} \tag{A41}$$

Consequently, the income share of middle-skill labor is:

$$Share_{M,t} = 1 - Share_{H,t} - Share_{L,t}. \tag{A42}$$

**Additional definitions for Home** The CPI-based real exchange rate is:

$$RER_t = \frac{P_t^*\mathbb{Q}_t}{P_t} \tag{A43}$$

Net exports-to-GDP ratio:

$$\frac{NX_t}{GDP_t} = \frac{\mathbb{Q}_t N_{X,t}\left(\tilde{w}_{X,t}\right)^{1-\theta}\hat{\mathbb{N}}_t^* - N_{X,t}^*\left(\tilde{w}_{X,t}^*\right)^{1-\theta}\hat{\mathbb{N}}_t}{P_t\hat{Y}_t} \tag{A44}$$

Exports-to-GDP ratio:

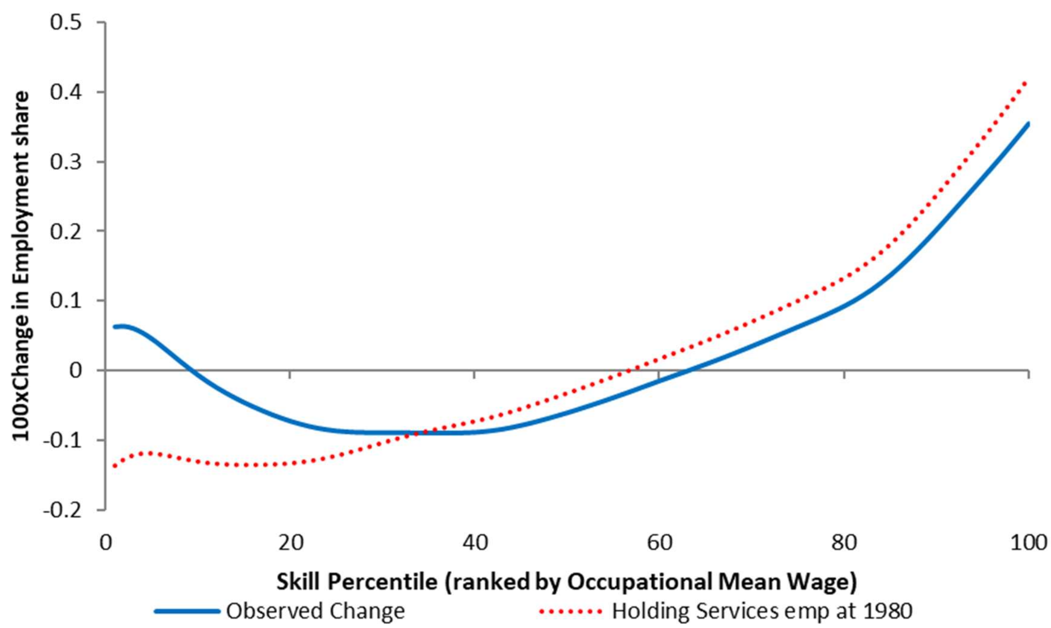
$$\frac{EX_t}{GDP_t} = \frac{\mathbb{Q}_t N_{X,t}\left(\tilde{w}_{X,t}\right)^{1-\theta}\hat{\mathbb{N}}_t^*}{P_t\hat{Y}_t} \tag{A45}$$

## 2 Data Sources and Bayesian Estimation

**Data sources for Fig. 1** Panels in Fig. 1 are constructed following the methodology in Autor and Dorn (2013). We use data from the American Community Survey (which includes 1% of the population) and the IPUMS census data (5% of the population) for the years 2021, 2007, 1980, respectively. Occupations are sorted into 100 percentiles based on the mean occupational wages in 1980.[2] The employment shares are computed for each occupation and then are aggregated at the percentile level. The change in employment shares is obtained as the simple difference between the share of employment for each year considered for the occupations in each percentile. For completeness, we consider a counterfactual changes in employment are calculated assuming that employment in all *service occupations* remains at the level of 1980. Mimicking the methodological approach in Autor and Dorn (2013), this counterfactual is constructed by pooling ACS data from 2007 with census data from 1980. This approach consists of estimating a weighted logit model for the odds, from which an observation is drawn from the 1980 census sample (relative to the actual sampling year), using as predictors a service occupation dummy and an intercept. Weights used are the product of census sampling weights and annual hours of labor supply. Observations in 2007 are re-weighted using the estimated odds multiplied by the hours-weighted census sampling weight, weighting downward the frequency of service occupations in 2007 to their 1980 level. Given the absence of other covariates in the model, the extra probability mass is implicitly allocated uniformly over the remainder of the distribution.

[2] As discussed in Acemoglu and Autor (2011), the ordering does not change significantly if a different base year is used.

Figure A1: Changes in Employment: The Role of Non-tradable Service Occupations




*Note:* Changes in employment by skill percentile. Red-dotted line: counterfactual in which *Service Occupations* remain constant at its 1980 level

**Data sources for model estimation** To estimate the model, we use data series for the interval from 1983:Q1 to 2018:Q4. First, we use the U.S. real GDP as a proxy for Home GDP; real GDP in the rest of the world as a proxy for Foreign GDP, which is constructed as a trade-weighted aggregate of the U.S. major trade partners; and Mexico's real GDP as a proxy for the South GDP.[3] The U.S. Census employment data used in Fig. 1 are decennial and thus not available on a high-frequency basis. In addition, the census data cannot be split easily into the three skill groups needed for the system estimation. Therefore, we closely follow Jaimovich and Siu (2020), and use the Current Population Survey from the Bureau of Labor Statistics) to construct quarterly time series of employment by skill group. We consider three categories of employment based on the skill content of the tasks executed by each occupation in the Census data: Non-Routine Cognitive (high-skill), Routine (middle-skill), and Non-Routine Manual (low-skill).[4] This classification is based on the categorization of occupations in the 2000 Standard Occupational classification system. *Non-routine cognitive* workers are in "management, business, and financial operations occupations" and "professional and related occupations." *Routine cognitive* workers are those in "sales and related occupations" and "office and administrative support occupations." *Routine manual* occupations are "production occupations", "transportation and material moving occupations," and "installation, maintenance, and repair occupations." *Non-routine manual* occupations are "service occupations" and "construction and extraction occupations." As explained in Jaimovich and Siu (2020) and Firpo et al. (2011), this group classification corresponds to rankings in the occupational income distribution: non-routine cognitive occupations tend to be high-skill occupations whereas non-routine manual occupations tend to be low-skill. Routine occupations both cognitive and manual are middle-skill occupations. The data are seasonally adjusted with the X-12 ARIMA method from the U.S. Census Bureau.

The categorization of occupations in our paper is slightly different than that in Jaimovich and Siu (2020). Specifically, construction occupations are grouped among those providing low-skill/non-tradable tasks, for two reasons. First, construction jobs are intrinsically non-tradable and thus not subject to offshorability. Second, even though the average hourly earnings of construction workers belong to the middle (and not the bottom) of earnings distributions in the CPS classification, some important caveats exist. The underground economy is particularly pervasive

[3]The U.S. trade partners included are: among the advanced economies, Australia, Canada, the euro area (Germany, France, Italy, Netherlands, Belgium, Spain, Ireland, Austria, Finland, Portugal, Greece), Japan, Sweden, Switzerland and the U.K.; among the emerging markets, China, India, Hong Kong, Taiwan, Korea, Singapore, Indonesia, Malaysia, Philippines, Thailand, Mexico, Brazil, Argentina, Venezuela, Chile, Colombia, Israel, Russia and Saudi Arabia. The data are collected from Haver Analytics.

[4]Jaimovich and Siu (2012) show that their classification in three groups is consistent with the analysis in Autor and Dorn (2012), which provides a more comprehensive definition of six categories based on an occupation's degree of intensity in abstract, routine, and manual tasks, respectively.

in this sector. Construction is densely populated by low-skill laborers who execute non-routine manual tasks that hardly can be mechanized. Many contractors are unregistered workers, and many of the registered ones subcontract by hiring hourly low-wage laborers without keeping records.[5] Having said this, the model implications are somewhat similar when construction occupations are included within the middle-skill segment.

To evaluate the model fit, we build and use two series that serve as proxies for (i) the inflows of low-skill migrant workers and (ii) the cost of offshoring. The series of apprehensions at the U.S.-Mexico border are constructed as follows: For January 1980 to September 2004, we use monthly data on apprehensions at the U.S.-Mexico border provided by the U.S. Immigration and Naturalization Service and made available on Gordon Hanson's website ("border linewatch apprehensions"). For October 1998 to September 2019, we use monthly data on apprehensions provided by the U.S. Border Patrol. We seasonally-adjust the monthly series and convert them to quarterly values using a cubic spline.

**Estimation Methodology** This section briefly explains the estimation approach used in this paper. A more detailed description of the method can be found in Justiniano and Preston (2010), among others. Let's define $\Theta$ as the parameter space of the DSGE model, and $z^T = \{z_t\}_{t=1}^T$ as the data series used in the estimation. Their joint probability distribution, $P(z^T, \Theta)$, results in a relationship between the marginal, $P(\Theta)$, and the conditional distribution $P(z^T|\Theta)$, which is known as the Bayes theorem: $P(\Theta|z^T) \propto P(z^T|\Theta)P(\Theta)$. The method updates the a prior distribution using the likelihood to obtain the conditional posterior distribution of the structural parameters in the data. The resulting posterior density $P(\Theta|z^T)$, is used to draw statistical inference on the parameter space, $\Theta$. Combining the state-form representation implied by the solution for the linear rational expectation model and the Kalman filter, we can compute the likelihood function. The likelihood and the prior permit a computation of the posterior that can be the starting value of the random walk version of the Metropolis-Hastings (MH) algorithm, which is a Monte Carlo method that generates draws from the posterior distribution of the parameters. In this case, the results reported are based on 100,000 draws from this algorithm. We choose a normal jump distribution with covariance matrix equal to the Hessian of the posterior density evaluated at the maximum. The scale factor is chosen to deliver an acceptance rate between 35% and 50% depending on the run of the algorithm. Measures of uncertainty follow from the percentiles of the draws.

**Smoothing** The DSGE model can be written in a state-space representation as $\xi_{t+1} = F\xi_t + v_{t+1}$ and $z_t = H'\xi_t + w_t$, in which $\xi_t$ is the vector of unobserved variables at date $t$, and $z_t$ is the vector of observables; shocks $v_t$ and $w_t$ are uncorrelated, normally distributed, white noise vectors. The first expression is the *state* equation, and the second is the *observed* equation.

Smoothing involves the estimation of $\xi^T = \{\xi_t\}_{t=1}^T$, conditional on the full data set, $z^T$, used in the estimation. The smoothed estimates are denoted as $\xi_{t|T} = E(\xi_t|z^T)$ and, as shown in Bauer et al. (2003), can be written as:

$$\xi_{t|T} = \xi_{t|t} + P_{t|t}F'P_{t+1|t}^{-1}\left[\xi_{t+1|T} - \xi_{t+1|t}\right], \tag{A46}$$

in which $P_{t+1|t} = E(\xi_{t+1} - \xi_{t+1|t})(\xi_{t+1} - \xi_{t+1|t})'$ is the mean squared forecasting error associated with the projection of $\xi_{t+1}$ on $z^t$ and a constant, projection which is denoted as $\xi_{t+1|t} = E(\xi_{t+1}|z^t)$. Using the Kalman filter to calculate, $\{\xi_t\}_{t=1}^T$, $\left\{\xi_{t+1|t}\right\}_{t=0}^{T-1}$, $\left\{P_{t|t}\right\}_{t=1}^{T}$, and $\left\{P_{t+1|t}\right\}_{t=0}^{T-1}$, the sequence of smooth estimates, $\left\{\xi_{t|T}\right\}_{t=1}^{T}$, is determined from equation (A46).

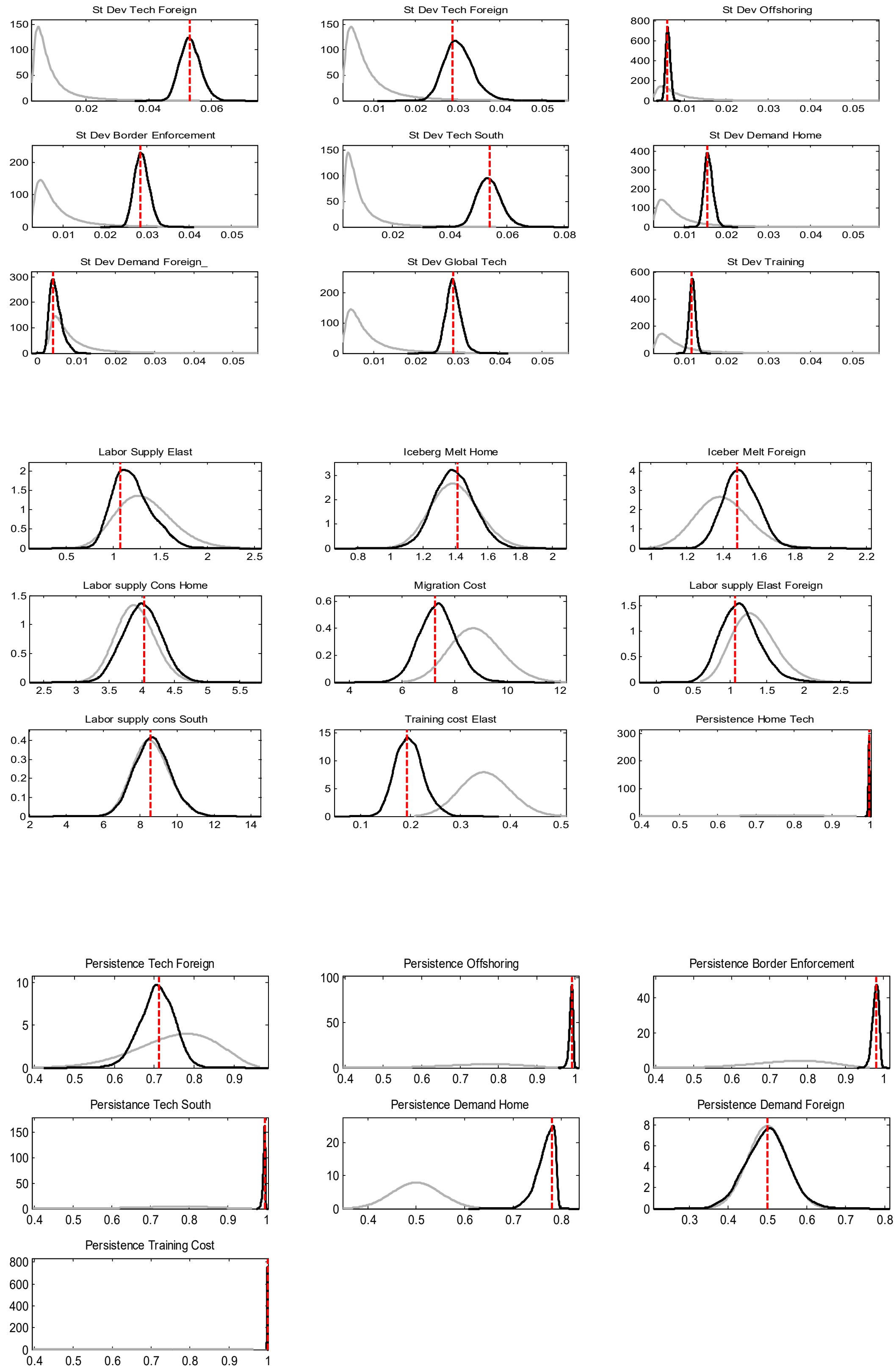
## 3 Additional Estimation Results for Baseline Model

**Prior and posterior density** Fig. A2 shows the prior density (grey line), posterior density (black line), and the mode (red line) from the numerical optimization of the posterior kernel for the benchmark model. These results complement those reported in Table 1 of the paper.

**Convergence diagnostics** Fig. A3 shows the convergence of iterative simulations with the multivariate diagnostic methods described in Brooks and Gelman (1998). The empirical 80% interval for any given parameter,

[5]For instance, a FPI report (2007) shows that despite the residential construction boom of the early 2000s in the New York City metropolitan area in which construction permits more than doubled, there was negligible increase in the official count of the New York City residential construction workers (which contradicts the evidence). In a related paper, Hotchkiss and Quispe-Agnoli (2012) find that the construction industry is, proportionally, the largest employer of undocumented immigrants. See also Cebula and Feiger (2011).

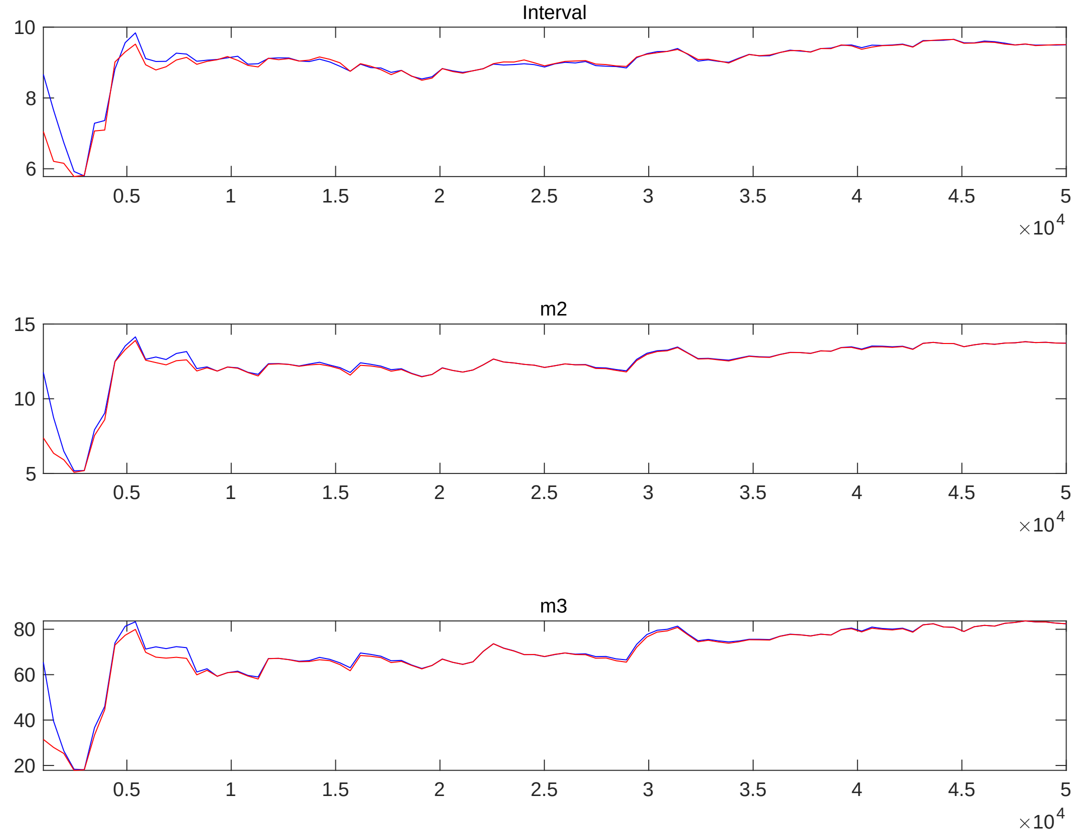
Figure A2: Prior and posterior distributions




*Note:* This figure shows the prior density (grey line), posterior density (black line), and the mode (red line) from the numerical optimization of the posterior kernel for the benchmark model.

$\varrho$, is first taken from each individual chain. The interval is described by the 10% and 90% of the $n$ simulated draws. In this multivariate approach, $\varrho$ is defined as a vector parameter based upon observations, $\varrho_{jt}^{(i)}$, denoting the $i_{th}$ element of the parameter vector in chain $j$ at time $t$. The direct analogue of the univariate approach in higher dimensions is to estimate the posterior variance-covariance matrix as: $\hat{V} = \frac{n-1}{n}W + (1+\frac{1}{m})B/n$, where $W = \frac{1}{m(n-1)}\sum_{j=1}^{m}\sum_{t=1}^{n}(\varrho_{jt} - \bar{\varrho}_{j\cdot})(\varrho_{jt} - \bar{\varrho}_{j\cdot})'$ and $B/n = \frac{1}{m-1}\sum_{j=1}^{m}(\bar{\varrho}_{j\cdot} - \bar{\varrho}_{\cdot\cdot})(\bar{\varrho}_{j\cdot} - \bar{\varrho}_{\cdot\cdot})'$. It is possible to summarize the distance between $\hat{V}$ and $W$ with a scalar measure that should approach 1 (from above) as convergence is achieved, given suitably over-dispersed starting points. We can monitor both $\hat{V}$ and $W$, determining convergence when any rotationally invariant distance measure between the two matrices indicates that they are sufficiently close. Fig. A4 reports measures of this aggregate.[6] Convergence is achieved before 100,000 iterations. General univariate diagnostics are not displayed, but they are available on request.

Figure A3: Convergence diagnostics



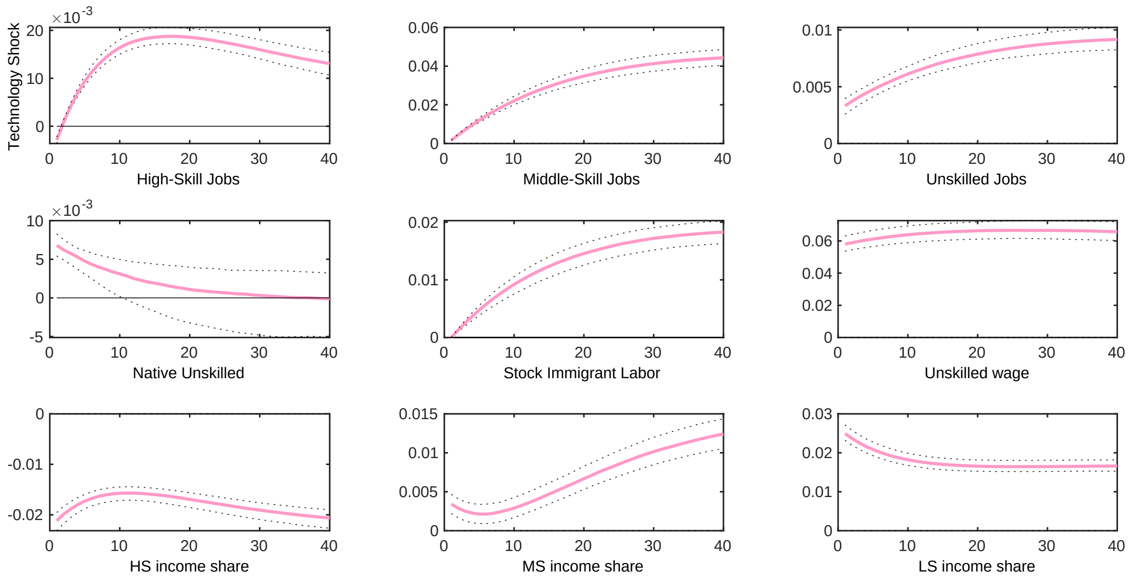

*Note:* This figure shows the convergence of iterative simulations with the multivariate diagnostic methods described in Brooks and Gelman (1998).

**Impulse responses** Fig. A4-A8 show additional impulse responses for technology and demand shocks. They are consistent with the model implications discussed in the paper. In Fig. A4, a positive technology shock in the Home "tradable" sector boosts the number of high-skill and middle-skill occupations and encourages task/skill upgrading among natives. As low-skilled native employment declines, immigration from the South is enhanced. In Fig. A5, a positive technology shock in foreign tradables tasks leads to a decrease in the number high-skill occupations in Home, which are substituted with relative more productive high- and middle-skilled foreign tasks. In contrast, the number of middle-skill occupations in Home which provide tasks only domestically increases. Since Home consumption receives a boost from the higher productivity in Foreign, the existing complementarity between goods and services prompts an increase in the low-skill native employment and immigration into Home. In Fig. A6, a positive technology shock in the Southern economy, where the immigrant labor originates, leads to a decrease

[6]Note that, for instance, the interval-based diagnostic in the univariate case becomes now a comparison of volumes of total and within-chain convex hulls. Brooks and Gelman (1998) propose to calculate for each chain the volume within 80%, say, of the points in the sample and compare the mean of these with the volume from 80% of the observations from all samples together.

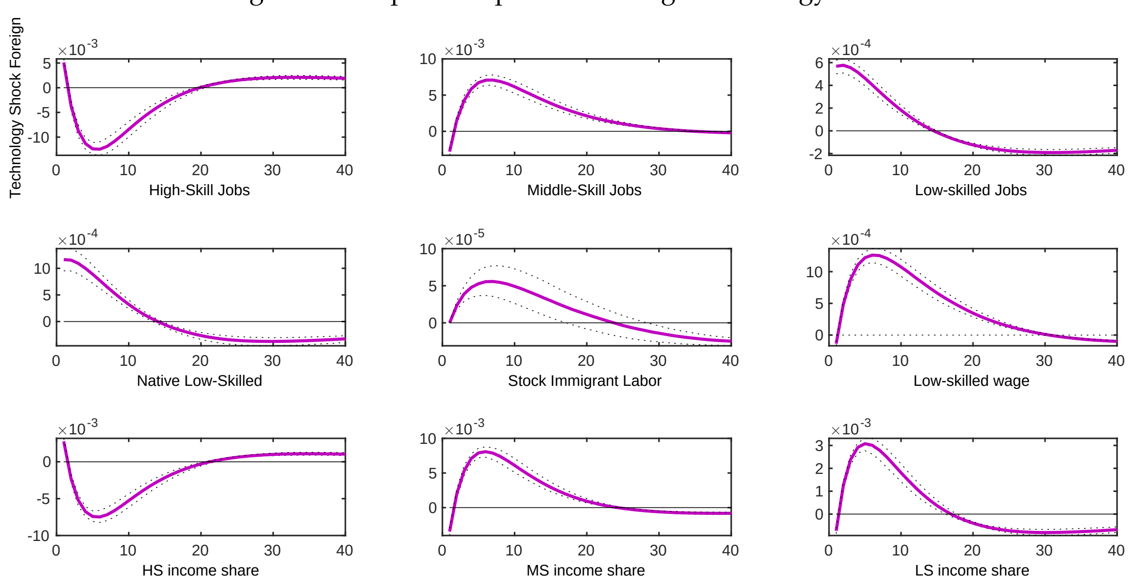
in the stock of immigrant labor in Home. The lower supply of immigrant labor also causes "task downgrading" in Home, i.e., the native workers reduce training, which leads to a decrease in the number of high-skill and middle-skill occupations, as well as to an increase in the low-skilled native employment in Home. In Fig. A7, a positive demand shock in Home, which encourages current consumption at the expense of future consumption, leads to an increase the number of high-skill occupations in Foreign (not shown), and–due to complementarity between goods and services–also to an increase in the low-skill native employment in Home. Similarly, in Fig. A8, a positive demand shock in Foreign leads to an increase the number of high-skill occupations in Home and an decrease in low-skilled native employment in Home.

Figure A4: Impulse response to Home technology shock



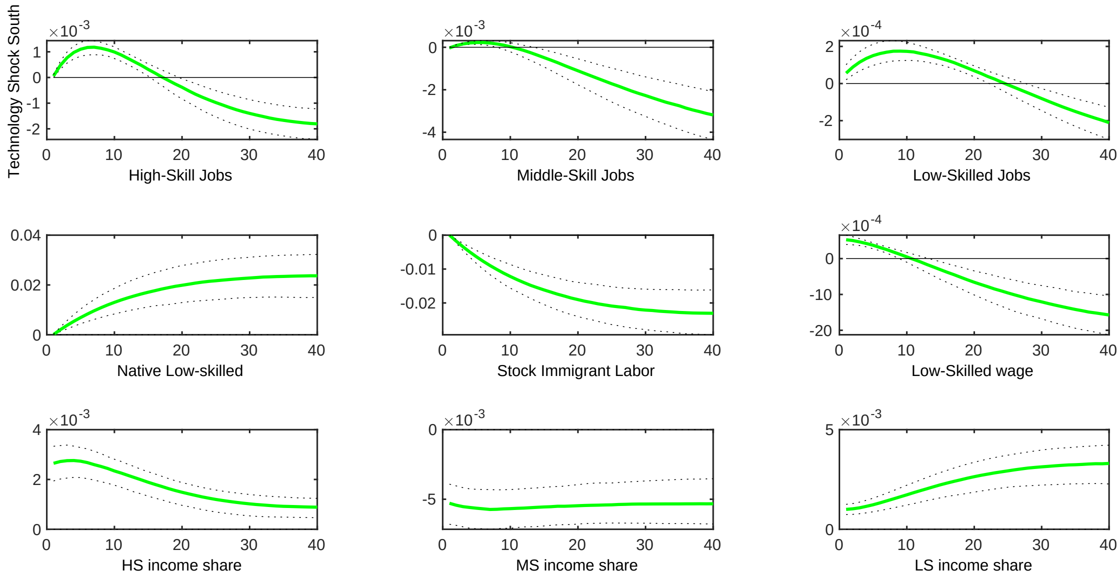

*Note:* This figure illustrates the impulse response of selected variables to the technology shock in Home. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percentiles.

Figure A5: Impulse response to Foreign technology shock



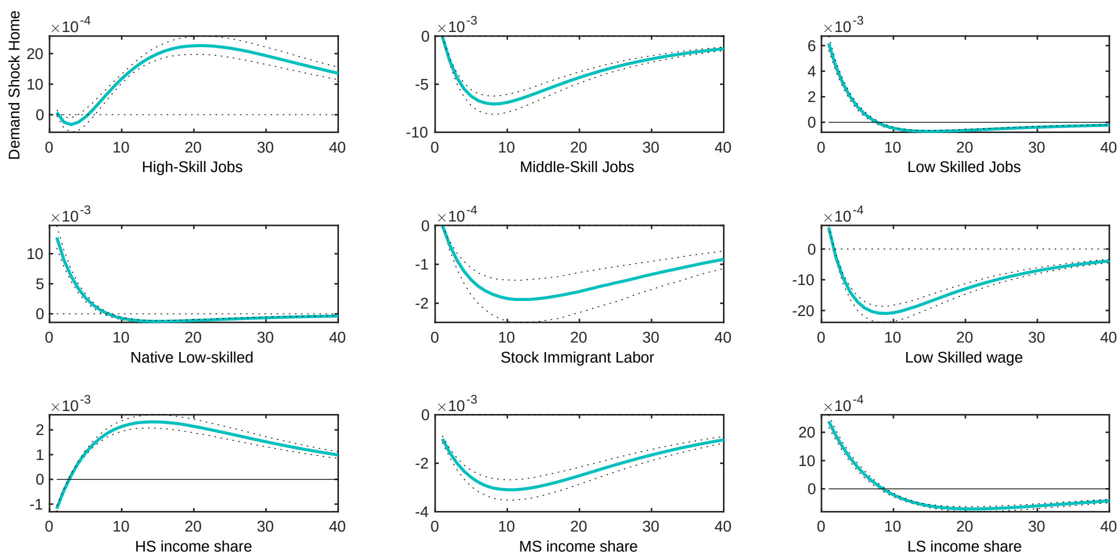

*Note:* This figure illustrates the impulse response of selected variables to the technology shock in Foreign. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percentiles.

Figure A6: Impulse response to South technology shock




*Note:* This figure illustrates the impulse response of selected variables to the technology shock in South. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percentiles.

Figure A7: Impulse response to Home demand shock

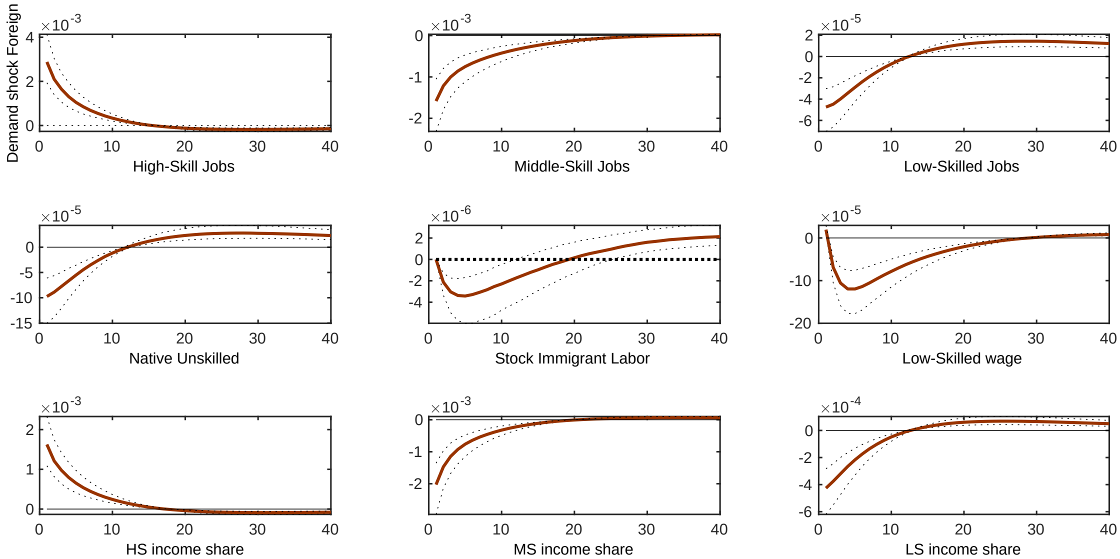



*Note:* This figure illustrates the impulse response of selected variables to the demand shock in Home. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percentiles.

**Variance decomposition** Fig. A9 displays the forecast error variance decomposition of key economic variables at various quarterly horizons (Q1, Q4, Q16, and Q40), based on the benchmark posterior estimation. As discussed, the model identifies shocks affecting the iceberg offshoring cost (cross-country symmetric), the sunk migration cost, training costs, technology, and consumption demand.

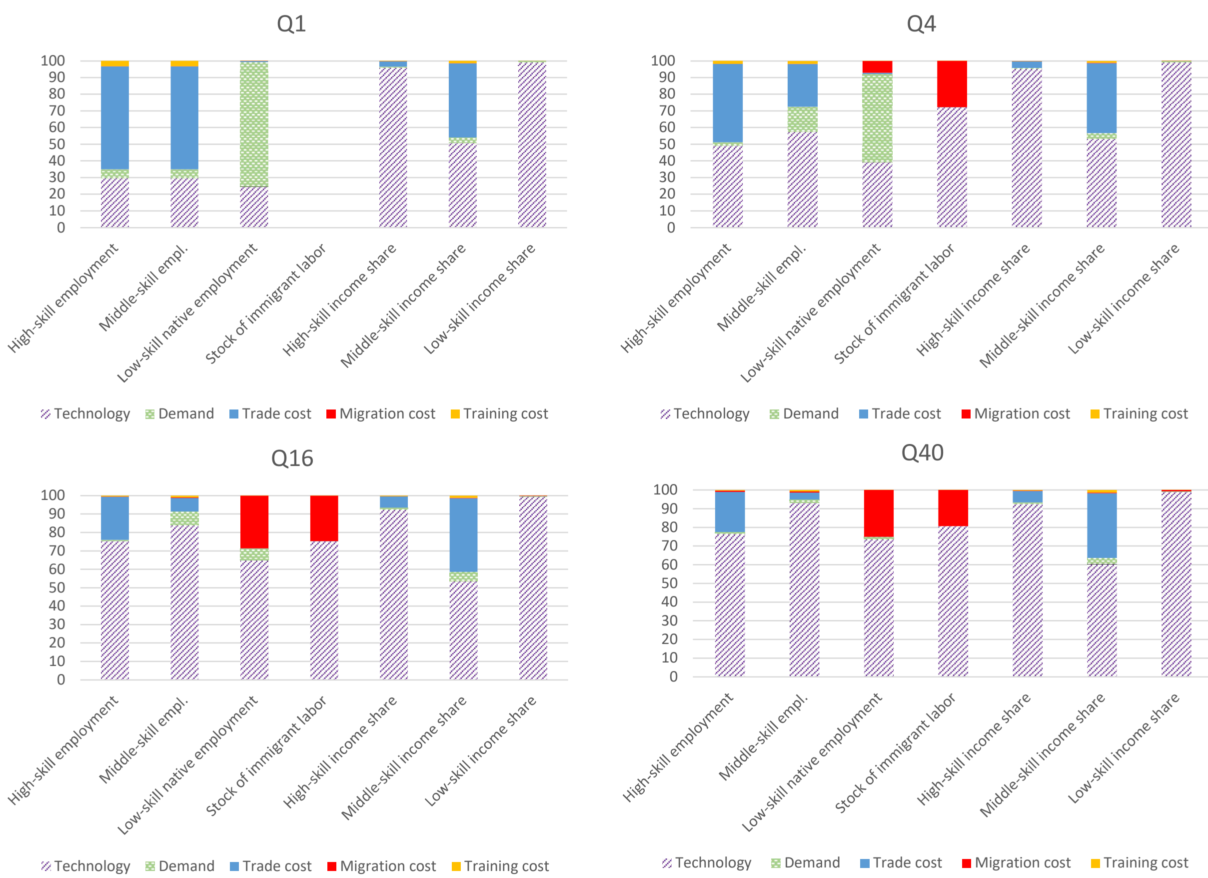
In the model, the high-skill and middle-skill employment in the tradable sector are rendered as state variables by the sunk training cost. Therefore, the estimated technology and demand shocks have small effects on these variables at very short horizons, while the shock to the iceberg trade cost have sizable effects on the offshoring margin in the short term. In contrast to high- and medium-skill employment, the low-skill employment (reflecting demand for services) reacts on impact to demand shocks. However, the impact of shocks to the iceberg trade cost and demand on the three types of employment tends to decline over time, in favor of shocks to productivity that become increasingly important.

Figure A8: Impulse response to Foreign demand shock




*Note:* This figure illustrates the impulse response of selected variables to the demand shock in Foreign. The solid line is the median impulse response to one standard deviation of the estimated shock, the dotted lines are the 10 and 90 percentiles.

Figure A9: Forecast error variance decomposition



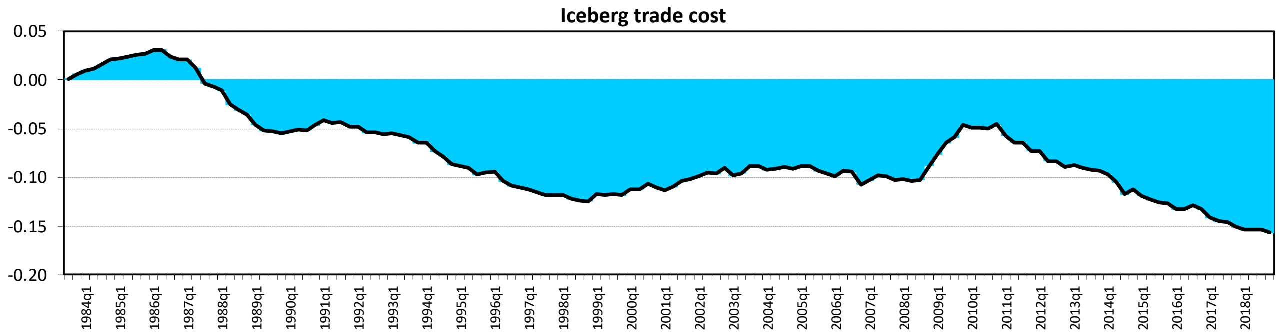

*Note:* This figure shows the forecast error variance decomposition of key economic variables at various quarterly horizons (Q1, Q4, Q16, and Q40), based on the benchmark posterior estimation.

The stock of immigrant labor does not react to shocks on impact, but reacts to technology and border enforcement shocks at both medium- and long-term horizons. Due to the substitutability between low-skill native and immigrant employment, the shock to border enforcement similarly affects the low-skill native employment at medium- and long-term horizons.

Finally, the income shares of high-skill and middle-skill labor are affected by shocks to technology and the iceberg trade cost, just like their corresponding employment groups. The shocks to border enforcement have little effect on the low-skill income share, since the latter includes both native and immigrant labor.

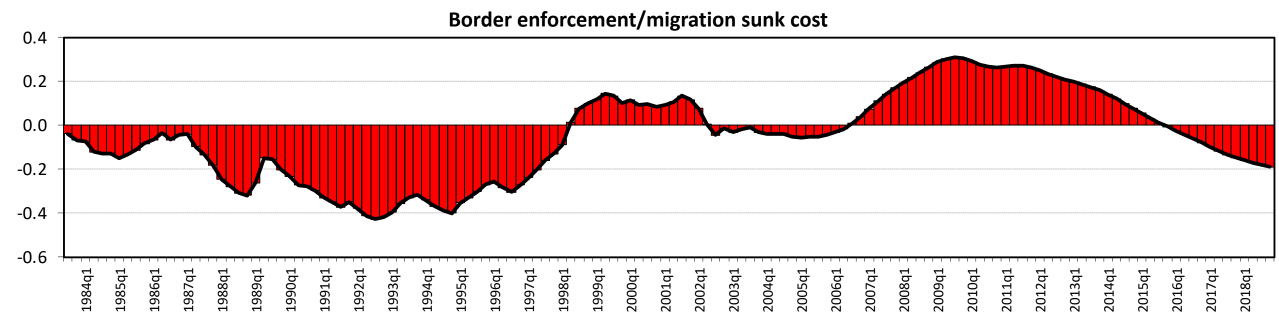
# 4 Additional figures

Figure A10: Shock to iceberg trade costs



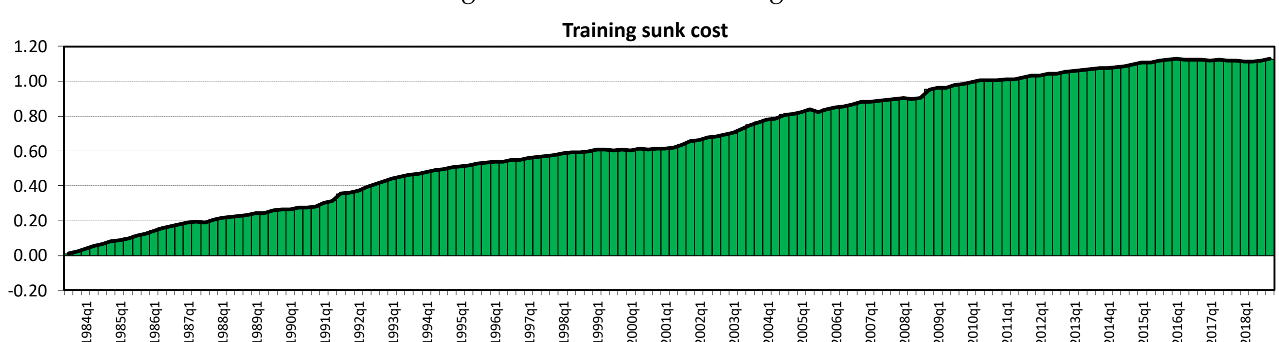

*Note:* This figure shows the shock to iceberg trade cost, which is disciplined with the ESCPAP/WB data.

Figure A11: Shock to sunk migration costs




*Note:* This figure shows the shock to sunk migration costs, which is disciplined with Border enforcement data.

Figure A12: Shock to training costs




*Note:* This figure shows the shock to training costs disciplined with Tuition CPI data.

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