

# The Allocation of Immigrant Talent: Macroeconomic Implications for the U.S. and Across Countries\*

Serdar Birinci  
St. Louis Fed

Fernando Leibovici  
St. Louis Fed

Kurt See  
Bank of Canada

January 2024

## Abstract

We quantify the labor market barriers that immigrants face, using an occupational choice model with natives and immigrants of multiple types subject to wedges that distort their allocations. We find sizable output gains from removing immigrant wedges in the U.S., representing 25% of immigrants' overall economic contribution, and that these wedges alter the impact of alternative immigration policies. We harmonize microdata across 19 economies and exploit cross-country variation in immigrant outcomes and estimated wedges to examine the drivers of differences in wedges and gains from their removal. Finally, we relate the estimated wedges with external cross-country measures of immigrant barriers.

Keywords: Immigration, occupational barriers, mobility, misallocation  
JEL Codes: J24, J31, J61

---

\*Birinci: [birincise@gmail.com](mailto:birincise@gmail.com), Leibovici: [fleibovici@gmail.com](mailto:fleibovici@gmail.com), See: [kurtgerrardsee@gmail.com](mailto:kurtgerrardsee@gmail.com). We thank participants at many seminars and conferences for their useful comments and suggestions. We also thank Aaron Amburgey, Jason Dunn, and Ngan Tran for excellent research assistance and Lydia Johnson and Jennifer Ives for excellent editorial assistance. This research was supported through computational resources provided by the Big-Tex High Performance Computing Group at the Federal Reserve Bank of Dallas. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Bank of Canada.

# 1 Introduction

Increased immigration holds the potential to be an important source of economic well-being across countries. For instance, by boosting countries' labor supply and stock of human capital, immigrants can have a substantial impact on innovation, growth, and fiscal sustainability. Yet, immigrants often face severe barriers to integrating into foreign labor markets, preventing them from working in the occupations in which they are most productive. Immigrants' productive potential is often limited by occupational regulations and licensing or discrimination, among other barriers. While there is extensive micro-level evidence on various types of specific barriers that immigrants face, understanding their overall macroeconomic effects has remained elusive.

In this paper, we ask two questions. First, what are the aggregate and distributional implications of immigrant labor market distortions both in the U.S. and in other countries? Second, how does the presence of these distortions affect the outcomes of immigration policy reforms?

In answering these questions, we make three key contributions. First, we develop an occupational choice model à la Roy (1951) featuring natives and immigrants, with the latter facing wedges that distort their allocations. Importantly, the model differentiates immigrants along relevant dimensions of heterogeneity, including education, language ability, origin country, and time since immigration. Second, we document novel evidence on immigrants' labor market outcomes from U.S. and harmonized cross-country microdata and use it to quantify the size of distortions faced by heterogeneous immigrants across countries. Third, we use our U.S. and cross-country estimates of immigrant distortions to understand the macroeconomic gains of removing immigrant barriers, the sources of these gains, and how existing barriers alter the effects of immigration policies. Importantly, we relate our model-derived estimates of immigrant wedges to external measures of barriers such as occupational licensing requirements in the U.S. and indices of individual attitudes and government policies toward immigrants across countries.

We highlight four novel findings of the paper. First, we find sizable and heterogeneous immigrant wedges and productivities. For instance, recent immigrants and those from low-income countries are estimated to be more productive than natives in manual occupations, but these immigrant types also observe the largest wedges in these occupations. Second, immigrant wedges in the U.S. have sizable aggregate implications, with their removal resulting in a 7% increase in real GDP, which is equivalent to 25% of immigrants' overall economic contribution. These gains are achieved through the entry of non-employed immigrants into employment mostly in manual occupations, the reallocation of employed immigrants from routine to non-routine occupations, and the increase in average hours worked. Third, we find that immigrant barriers are pervasive across countries and often much larger than in the U.S. We exploit cross-country variation in immigrant labor market outcomes in the data and estimated wedges in the model to further examine underlying drivers of wedges and the gains from their removal. We show that countries

with similar average distortions can have sizable differences in the gains from removing barriers because of differences in the rate of immigrant unemployment and the distribution of immigrant wedges affecting productive occupations or individuals. Finally, we find that the presence of immigrant barriers strongly affects the outcomes of immigration policy reforms. For example, the productivity gains from admitting new immigrants, especially those from disadvantaged groups (e.g. less-educated and from low-income countries), become especially larger when immigrant wedges are also removed upon their admission.

Our starting point is an equilibrium model populated by natives and immigrants. The model extends the quantitative framework developed by [Hsieh, Hurst, Jones, and Klenow \(2019\)](#) by modeling immigrants as in [Burstein, Hanson, Tian, and Vogel \(2020\)](#), and by introducing endogenous labor supply. We consider a static and closed economy with natives and immigrants of multiple types who choose among alternative occupations and hours worked, or to stay non-employed. Individuals of each type differ in productivity, preferences, and wedges across occupations. To model differences in productivity, we characterize each worker group (partitioned based on native and immigrant characteristics as well as demographics) by a productivity level in each occupation common across all individuals of the group. Thus, we allow the productivity of immigrants and natives to differ across occupations. Each individual also draws a vector of *idiosyncratic* productivities, one for each occupation, from a Frechet distribution whose shape parameter is disciplined to capture differences in productivity across natives and immigrants due to unobserved heterogeneity and immigrant selection.

All individuals, including natives, are subject to *(i)* compensation wedges modeled as proportional taxes that vary across occupations and *(ii)* heterogeneous preferences across occupations. In the model, immigrants differ from natives in two ways. First, immigrants face additional immigrant compensation wedges and immigrant labor supply wedges. These wedges are intended to capture a wide range of barriers that immigrants face in foreign labor markets. In the model, immigrant wedges distort the occupational and labor supply choices by discouraging employment altogether, by preventing the allocation of employed immigrants to their most-productive occupations, and by affecting hours worked. Second, the production of occupation-specific goods features imperfect substitution between native and immigrant workers.

We present findings on the joint distribution of employment, annual earnings, and hourly wages across individuals and occupations in the U.S, which we use to estimate the model. In particular, we use microdata from the American Community Survey (ACS) that provide detailed information about immigrants. We consider multiple immigrant types based on time since immigration, English fluency, and the income level of the origin country. We further partition natives and each immigrant type into subtypes based on education, age, and gender. We allocate individuals between a non-market (non-employment) occupation and 25 market occupations. As we show in our results, accounting for rich heterogeneity in worker groups and occupations turns

out to be pivotal in quantifying wedges and greatly amplifies the gains from their removal.

Our empirical findings reveal differences in the outcomes between natives and immigrants, as well as across immigrants. For example, immigrants are more likely to work in manual occupations such as cleaning and maintenance, construction, and services than natives. Among high-paid occupations, immigrants are more likely to work in computer and mathematical occupations but less likely to work in management than natives. With the exception of immigrants from high-income countries, immigrants systematically earn less in all occupations except for non-routine cognitive jobs. Within immigrants, a longer length of stay, better English proficiency, and originating from a higher-income country are all associated with higher earnings.

We use our model to identify whether these differences in the labor market outcomes of immigrants are accounted for by differences in productivities or by wedges. We show that all key parameters of the model, including wedges and productivities, can be estimated to match the joint distribution of employment, annual earnings, and hourly wages across individuals and occupations. Overall, our identification strategy follows the approach in [Hsieh et al. \(2019\)](#). In their setup, when two groups of workers share the same productivity distribution and the same distribution of preferences over occupations, their employment distributions across occupations should be identical in the absence of wedges. Thus, for example, if one group is less likely to be observed in an occupation and wages are the same, then it must mean that this group faces barriers in that occupation. We show that a similar logic also follows in our context once we assume that idiosyncratic productivities of natives and immigrants are drawn from a common distribution. We argue that this is a reasonable assumption given findings in [Martellini, Schoellman, and Sockin \(2023\)](#). They show that despite significant differences in the quality of education between rich and poor countries, the average human capital of immigrants is close to that of natives, as emigrants are more positively selected when migrating from poor economies.<sup>1</sup>

Using this strategy, we back out wedges given a very limited set of predetermined parameters and widely accessible data. This approach ensures the estimation of the model with rich levels of heterogeneity and allows us to obtain insights on the patterns of the data that identify wedges and productivities. We find that the estimated immigrant wedges and differences in productivities between natives and immigrants are sizable and vary systematically across immigrant types and occupations. For instance, new immigrants with lower English proficiency and who originate from low-income countries tend to be more productive than natives in manual occupations, yet these immigrant types also face the largest distortions in the said occupations.

To understand the macroeconomic implications of immigrant barriers, we contrast our estimated model of the U.S. economy with a counterfactual economy in which all immigrant wedges are removed—that is, immigrants face the same level of distortions as natives across occupations.

---

<sup>1</sup>Importantly, while we think that a common distribution for idiosyncratic productivity draws for immigrants and natives is an empirically reasonable assumption, we also provide our main results when we instead assume that these productivities are drawn from a different distribution for immigrants and natives.

We find that removing immigrant wedges increases real GDP by 7%. This increase results from three margins: an increase in employment among immigrants mostly in manual occupations, an increase in average hours worked among the employed, and a reallocation of employed immigrants from routine to non-routine jobs. In the aggregate, increases in productivity, employment, and hours worked all contribute to the rise in real GDP, but productivity accounts for the largest gains. By margin of adjustment, about a third of the output growth from removing barriers is caused by individuals moving in and out of non-employment. The rest of the gains are almost equally due to employed workers switching jobs and changing their hours. Additionally, we evaluate the quantitative significance of the output gain from removing barriers by expressing it as a fraction of immigrants' overall contribution to output. The gains from removing immigrant barriers are 25% of the total contribution of immigrants to U.S. output.

We show that the gains from removing immigrant wedges are heterogeneous across occupations and worker groups. Across occupations, the largest gains are seen in non-routine jobs, while the smallest gains are in routine occupations. The primary driver of larger gains in non-routine cognitive occupations is the rise in productivity, while in non-routine manual occupations it is the rise in employment. We find that upon removal of immigrant wedges, disadvantaged immigrant groups, such as recent immigrant or those with less education or English fluency, are more likely to experience transitions from non-employment to employment as well as across occupations compared with other immigrant types. Consistent with these findings, when we compute the impact of removing only the wedges faced by a particular immigrant group, we find that larger aggregate output gains are achieved when wedges are removed for these disadvantaged immigrant groups. On the other hand, we identify much smaller aggregate gains when wedges are removed only for immigrants who have been in the country for more than a decade (established immigrants) or those with strong English proficiency. Hence, our results imply that while newcomers face significant barriers, these barriers decay over time.

Given the pervasive and heterogeneous nature of immigrant barriers, we investigate how these barriers affect the outcomes of immigration policies. The gains from the entry of new immigrants—in spite of their skills and potential to fill labor supply gaps in key occupations—may be subdued if barriers prevent their allocation into the most suitable jobs. Thus, we study the effects of raising the mass of immigrants in the U.S. through the entry of new immigrants with alternative-type compositions. We highlight two important results on how immigrant wedges influence conclusions from such immigration policies. First, the productivity gains from admitting new immigrants significantly increase in the absence of immigrant barriers, implying that immigration policy should also consider immigrant outcomes after entry. Second, removing immigrant wedges at the time of admitting new immigrants also changes the ranking of productivity gains associated with the entry of immigrants with alternative compositions. For instance, while the productivity gains from admitting immigrants who are college educated, fluent in English, or

from high-income countries are larger than the gains from admitting disadvantaged immigrant groups (without a college degree, not fluent in English, or from low-income countries), the opposite becomes true if immigrant wedges are simultaneously removed upon admission.

An important advantage of our approach is that our analysis for the U.S. can be easily applied to many countries given micro-level data on labor market outcomes and demographics of immigrants and natives. Extending our analysis to cover many countries is valuable, as cross-sectional variation in labor market outcomes of immigrants and natives in the data and estimated immigrant wedges in the model help us provide further insights on underlying labor market moments that affect immigrant wedges and the gains from their removal. To do so, our first step allows us to make an important empirical contribution by providing harmonized target moments on the joint distribution of employment, annual earnings, and hourly wages of worker groups across occupations for 19 economies using the Luxembourg Income Study (LIS) database. We then use these moments to document how the sizes and distributions of immigrant wedges as well as the gains from their removal vary across countries. Our findings highlight substantial heterogeneity in the magnitude and impact of the barriers faced by immigrants across countries. For instance, countries such as the U.K. and Australia are estimated to feature both low immigrant wedges and gains from their removal, while those are estimated to be much higher for Spain and Greece. We find that the U.S. features levels of immigrant wedges and gains from removing them that are close to the average across the countries in our sample.

While the average magnitude of immigrant barriers is connected with the implied gains from removing them, we also find non-trivial heterogeneity in their impact, even across countries with similar average immigrant wedges. We show that much of this cross-country heterogeneity in the gains from removing immigrant wedges is accounted for by two key cross-country differences. Along the extensive margin, we find that countries with a higher fraction of non-employed immigrants feature significantly larger gains from removing immigrant wedges. Along the intensive margin, we find that the distribution of wedges across occupations and individuals plays an important role as well. That is, the gains from removing wedges are larger in economies where more-productive occupations or individuals are subject to larger wedges.

Finally, we demonstrate that our estimated immigrant wedges in the U.S. and across countries are consistent with external measures on the degree to which immigrants face labor market barriers. For the U.S., we show that model-implied immigrant wedges are positively correlated with the fraction of jobs requiring a license across occupations. Importantly, we find these correlations are much higher when we compare licensing requirements with immigrant wedges for recent immigrants, but the correlations disappear for established immigrants. This finding suggests that immigrant barriers due to occupational licensing requirements lessen over time. Across countries, we focus on two indexes that capture de facto barriers as reflected in individuals' attitudes toward immigrants and de jure barriers as reflected by governments' policies,

respectively. We find that our estimates of immigrant wedges are consistent with these indexes, as countries with better attitudes or policies toward immigrants exhibit lower immigrant wedges.

**Related literature.** Our paper contributes to a growing literature that studies the macroeconomic effects of immigration, using structural frameworks (Llull 2018; Burstein, Hanson, Tian, and Vogel 2020; Monras 2020; Albert 2021; Albert, Glitz, and Llull 2021; Albert and Monras 2021; Hanson and Liu 2021; Piyapromdee 2021). These papers develop quantitative models that are disciplined using U.S. microdata to analyze the impact of immigration on wages, occupational choice, migration, inequality, output, and welfare. We also develop a framework that accounts for differences in labor market outcomes between natives and immigrants of different types across occupations, to measure immigrant wedges, to quantify the gains from removing them, and to examine the implications for the effects of immigration policy. In addition to the U.S., we also study the prevalence and implications of immigrant barriers across countries. To the best of our knowledge, our paper is the first to document differences in labor market outcomes between natives and immigrants of various types across occupations in different countries, using these to estimate immigrant wedges and to study their macroeconomic and policy implications.

A separate literature examines labor market outcomes of immigrants when studying cross-country differences in human capital and productivity (Hendricks 2002; Schoellman 2012; Schoellman 2016; Hendricks and Schoellman 2018; Lagakos et al. 2018a; Martellini, Schoellman, and Sockin 2023). While our focus is different, our results have implications for studies in this literature, as we show that immigrant barriers often lower immigrants' productivity by preventing them from working in the occupations in which they are most productive and that the magnitude of these barriers as well as output losses due to their presence largely differ across countries.

Finally, our paper also contributes to a literature on the macroeconomic effects of the misallocation of factor inputs across production units, sectors, and occupations (Restuccia and Rogerson 2008; Hsieh and Klenow 2009; Buera, Kaboski, and Shin 2011; Bartelsman, Haltiwanger, and Scarpetta 2013; Hopenhayn 2014; Bento and Restuccia 2017; Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez 2017; Hsieh, Hurst, Jones, and Klenow 2019). Relative to this body of work, we focus on the misallocation of immigrants, which represents an increasing share of employment in host countries. We show that immigrants face substantial wedges that distort their labor supply decisions, with significant implications for aggregate outcomes.

This paper is organized as follows. Section 2 presents our model. Section 3 provides details on the data, estimation, and identification. Section 4 presents estimation results and discusses our findings for the U.S. Section 5 studies implications of immigrant wedges on immigration policies, and Section 6 extends our analysis to other countries. Section 7 provides a comparison between wedges with external measures on immigrant barriers, and Section 8 provides discussions for our main results under alternative model specifications. Finally, Section 9 concludes.

## 2 Model

In this section, we construct an occupational choice model á la Roy (1951) featuring natives and immigrants of multiple types. This framework extends the model in Hsieh et al. (2019) by incorporating immigrants as in Burstein et al. (2020).

We consider an economy populated by a continuum of individuals and a discrete number of occupations. Individuals choose their occupation and hours worked, and production in each occupation is carried out by a representative firm that hires their labor. A representative final-good producer aggregates the production from each occupation into a final good. Below, we describe the environment in which these agents operate.

### 2.1 Individuals

**Demographics.** We consider a static model in which individuals live for one period. They are partitioned into types  $i = 1, \dots, I$  based on their immigration status (e.g., natives and various types of immigrants based on time since immigration, English fluency, and the income level of their country of origin). We let  $i = 1$  denote natives and  $i = 2, \dots, I$  denote the set of immigrant types. Individuals of every given type  $i$  are further partitioned into subtypes  $g = 1, \dots, G$  based on observables such as age, gender, and education. We denote the mass of individuals of type  $i$  and subtype  $g$  by  $N_{ig}$ ; the total mass of individuals in the economy is  $N$ ,  $\sum_{i=1}^I \sum_{g=1}^G N_{ig} = N$ .

**Preferences, labor supply, and immigrant labor supply wedges.** Individuals of type  $i$  and subtype  $g$  supply  $\ell$  units of labor to work in occupation  $j = 0, \dots, J$ , and consume  $c$  units of the final good. Their preferences over consumption and labor supply are represented by the following utility function:  $u_{ig}^j(c, \ell) = (1 + \gamma_{ig}^j) \nu_g^j c - \frac{\ell^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}$ , where  $\xi$  denotes the Frisch elasticity,  $\nu_g^j$  is a preference shifter that is common across all individuals of subtype  $g$  who work in occupation  $j$ , and  $\gamma_{ig}^j$  is a wedge that distorts the occupational choices of all immigrants of type  $i$  and subtype  $g$ . Thus, we have that  $\gamma_{1g}^j = 0 \forall g, j$  since  $i = 1$  denotes native individuals. We refer to  $\gamma$  as an “immigrant labor supply wedge” since, conditional on labor market compensation, it distorts immigrants’ labor supply decisions across occupations relative to natives.

**Individual productivity across occupations.** The supply of labor by individuals is not equally productive in all occupations. An individual of type  $i$  and subtype  $g$  who chooses to supply  $\ell$  units of labor to work in occupation  $j$  supplies  $z_{ig}^j \varepsilon_j \ell$  effective units of labor, where  $z_{ig}^j$  is a productivity component common across all individuals of type  $i$  and subtype  $g$  that work in occupation  $j$ , while  $\varepsilon_j$  is an idiosyncratic occupation-specific productivity draw.

In particular, each individual of type  $i$  and subtype  $g$  is characterized by a vector of idiosyncratic productivities  $(\varepsilon_0, \dots, \varepsilon_J)$  for each of the occupations. These idiosyncratic productivities are distributed Fréchet with type-specific shape parameter  $\eta_i$  and *i.i.d.* across individuals and occupations. The joint cumulative distribution function (CDF) is thus given by



$F(\varepsilon_0, \dots, \varepsilon_j) = \exp\left(\sum_{j=0}^J \varepsilon_j^{-\eta_i}\right)$ . We model  $\eta_i$  as type-specific to capture potential underlying productivity differences between natives and immigrant types due to selection (Hendricks and Schoellman, 2018) or unobserved heterogeneity (e.g., due to differences in education quality across countries of origin as documented by Martellini, Schoellman, and Sockin, 2023, or due to differences across countries in the life-cycle accumulation of human capital as documented by Lagakos, Moll, Porzio, Qian, and Schoellman, 2018b) across individual types.

**Labor income and compensation wedges.** Individuals of type  $i$  and subtype  $g$  who work in occupation  $j$  are paid a wage  $w_{ig}^j$  per effective unit of labor. Yet, their labor income is subject to “compensation wedges” that distort their net income and occupational choices. We model compensation wedges as proportional taxes (or subsidies) on the labor income. All individuals of subtype  $g$  that work in occupation  $j$  are subject to compensation wedge  $\tau_g^j$ . Immigrants of type  $i = 2, \dots, I$  are additionally subject to “immigrant compensation wedges”  $\kappa_{ig}^j$ . Thus,  $\kappa_{1g}^j = 0 \forall g, j$  since  $i = 1$  denotes native individuals. We assume that the aggregate revenue collected through these wedges is reimbursed as a proportional subsidy  $s$  paid to all individuals.

In this framework, we model two sources of immigrant labor market distortions (i.e., labor supply and compensation wedges) to account for the possibility that the occupational choices of immigrants may be distorted even when compensation differences are controlled for. That is, the inclusion of both wedges allows us to capture the fact that immigrants may be prevented from working in certain occupations for two reasons.

**Occupational choice** An individual with a vector of idiosyncratic productivities  $(\varepsilon_0, \dots, \varepsilon_J)$  chooses occupation  $j^*$  and labor supply  $\ell^*$  that solve the following problem:

$$\max_{j \in \{0, \dots, J\}, \ell} (1 + \gamma_{ig}^j) \nu_g^j c - \frac{\ell^{1+\frac{1}{\xi}}}{1 + \frac{1}{\xi}} \quad s.t. \quad pc = (1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j \ell z_{ig}^j \varepsilon_j \times (1 + s),$$

where  $p$  denotes the price of the final good. The right-hand side of the budget constraint is individual labor income net of compensation wedges  $\tau_g^j$  and  $\kappa_{ig}^j$ , along with reimbursement  $s$ .

## 2.2 Occupations

Production in each occupation  $j = 0, \dots, J$  is carried out by an occupation-specific representative firm. Occupation  $j = 0$  is the non-market occupation (i.e., work at home as in Hsieh et al. 2019), while the rest,  $j = 1, \dots, J$ , are market occupations.

We model the difference between market and non-market occupations by assuming that they differ in their production technologies. Production in market occupations is carried out through a nested constant elasticity of substitution (CES) technology that aggregates different types of labor to produce an occupation-specific good. In contrast, production in the non-market occupation is carried out through a linear technology, capturing the idea that this occupation encompasses home production activities that could be done independently by each individual.

### 2.2.1 Market occupations

Following [Burstein et al. \(2020\)](#), the production technology is a nested CES, with two nests that are aggregated as follows. The outer nest aggregates labor bundles across two groups based on immigration status, natives (individual type  $i = 1$ ) and all types of immigrants (individual types  $i = 2, \dots, I$ ), with an elasticity of substitution  $\sigma_j$ . For each of these groups, there is an inner nest that aggregates labor bundles across the various types ( $i = 1$  for the native group and  $i = 2, \dots, I$  for the immigrant group) and all subtypes  $g$  with elasticity of substitution  $\tilde{\sigma}_j$ . That is, each inner nest combines labor across demographic subtypes (e.g., age, gender, education) within the given immigration-based group (e.g., natives or immigrants).

**Outer nest: Aggregation between natives and immigrants.** The production technology for the outer nest aggregates labor bundles between natives and immigrants with a CES technology with elasticity  $\sigma_j$ :  $y_j = A_j [n_{\text{nat}}^j \frac{\sigma_j - 1}{\sigma_j} + n_{\text{imm}}^j \frac{\sigma_j - 1}{\sigma_j}]^{\frac{\sigma_j}{\sigma_j - 1}}$ , where  $y_j$  denotes the output produced in occupation  $j$ ,  $n_k^j$  denotes the labor bundle of group  $k$  in occupation  $j$ , and  $A_j$  denotes occupation-specific productivity. We index natives and immigrants with subscripts  $k = \text{nat}$  and  $k = \text{imm}$ , respectively.<sup>2</sup>

The problem of the representative producer in market occupation  $j = 1, \dots, J$  involves maximizing profits by choosing the amount of labor bundles of each group to hire, taking as given the price of the good sold and the wage rate of each labor bundle. The problem is given by:

$$\max_{y_j, n_{\text{nat}}^j, n_{\text{imm}}^j} p_j y_j - w_{\text{nat}}^j n_{\text{nat}}^j - w_{\text{imm}}^j n_{\text{imm}}^j \quad s.t. \quad y_j = A_j \left[ n_{\text{nat}}^j \frac{\sigma_j - 1}{\sigma_j} + n_{\text{imm}}^j \frac{\sigma_j - 1}{\sigma_j} \right]^{\frac{\sigma_j}{\sigma_j - 1}},$$

where  $p_j$  denotes the price of the good produced by occupation  $j$ , and  $w_k^j$  denotes the cost of labor bundle  $k$  hired by occupation  $j$ .

**Inner nest: Aggregation within natives and immigrants.** The production technology for the inner nest produces labor bundles for group  $k \in \{\text{nat}, \text{imm}\}$  by aggregating workers of all types  $i \in \mathcal{I}_k$  and all subtypes  $g$  with a CES technology with elasticity  $\tilde{\sigma}_j$  for each  $k \in \{\text{nat}, \text{imm}\}$ :  $n_k^j = [\sum_{i \in \mathcal{I}_k} \sum_{g=1}^G n_{ig}^j \frac{\tilde{\sigma}_j - 1}{\tilde{\sigma}_j}]^{\frac{\tilde{\sigma}_j}{\tilde{\sigma}_j - 1}}$ , where  $\mathcal{I}_{\text{nat}} = \{1\}$ ,  $\mathcal{I}_{\text{imm}} = \{2, \dots, I\}$  and  $n_{ig}^j$  denotes the effective units of labor hired from individuals of pair  $(i, g)$  in occupation  $j$ .

The problem of the representative producer of labor bundles of group  $k \in \{\text{nat}, \text{imm}\}$  in market occupation  $j = 1, \dots, J$  consists of maximizing profits by choosing the total effective units of labor of each type and subtype to hire, taking as given the price of the labor bundle and wage rates in occupation  $j$ . The problem is then given by:

---

<sup>2</sup>We also study two alternative production technologies. In the first, the outer nest aggregates natives and immigrants across different education levels. Specifically, the outer nest aggregates labor bundles across natives with a college degree, natives without a college degree, immigrants with a college degree, and immigrants without a college degree. In the second, the outer nest aggregates labor bundles across natives and each different type of immigrant. In [Appendix E](#), we discuss the implications of these alternative specifications.

$$\max_{n_k^j, \{n_{ig}^j\}_{i \in \mathcal{I}_k, g}} w_k^j n_k^j - \sum_{i \in \mathcal{I}_k} \sum_{g=1}^G w_{ig}^j n_{ig}^j \quad s.t. \quad n_k^j = \left[ \sum_{i \in \mathcal{I}_k} \sum_{g=1}^G n_{ig}^j \frac{\tilde{\sigma}_j - 1}{\tilde{\sigma}_j} \right]^{\frac{\tilde{\sigma}_j}{\tilde{\sigma}_j - 1}},$$

where  $w_{ig}^j$  is the wage rate per effective unit of labor for pair  $(i, g)$  in occupation  $j$ .

### 2.2.2 Non-market occupation

Production in the non-market occupation  $j = 0$  is carried out by a representative firm using labor of any type and subtype. The production technology is linear in the total effective units of labor with occupation-specific productivity  $A_0$ . The problem of this firm consists of maximizing profits by choosing the total effective units of labor hired  $n^0$  given the price of the good sold  $p_0$  as well as the occupation-specific wage rate  $w^0$ . The problem is given by:

$$\max_{y_0, n^0} p_0 y_0 - w^0 n^0 \quad s.t. \quad y_0 = A_0 n^0.$$

## 2.3 Final good producer

The final good is produced by a representative firm that aggregates the goods produced across all occupations by operating a CES technology with elasticity  $\sigma$ .

The problem of the final-good producer consists of maximizing profits by choosing the amount of goods to purchase from each of the occupations  $y_j$ , taking as given the price of the final good  $p$  as well as prices of occupation-specific goods  $p_j$ . The problem is then given by:

$$\max_{y, \{y_j\}_{j=0}^J} py - \sum_{j=0}^J p_j y_j \quad s.t. \quad y = \left[ \sum_{j=0}^J y_j^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

## 2.4 Equilibrium

We provide a formal definition of equilibrium in Appendix A. The equilibrium of this model consists of prices and allocations such that (i) individuals and firms solve their problem taking prices as given; (ii) revenue collected through compensation wedges is equal to reimbursements distributed to individuals; (iii) labor markets for each (type, subtype) pair in each occupation clear; and (iv) the final good market clears.

# 3 Estimation

## 3.1 Data

We estimate the model using U.S. data from the American Community Survey (ACS) between 2010 and 2019.<sup>3</sup> We restrict our sample to non-business owners between the ages of 25 and 54. This sample restriction allows us to focus on working-age individuals who have finished schooling

---

<sup>3</sup>We pool all ten years together to increase the sample size and treat them as one cross section.

but are prior to retirement. We also drop individuals on active military duty. Appendix B.1 provides details about the data, construction of variables, and measurement.

**Individual types.** We partition individuals in the data into the  $I$  individual types outlined in the model, which we index by  $i = 1, \dots, I$ . We let  $i = 1$  denote the set of natives and let  $i = 2, \dots, I$  denote the partition of immigrants based on time since immigration, English fluency, and the home country’s income level. We define immigrants as the set of foreign-born individuals.<sup>4</sup>

We partition immigrants’ time since immigration based on their arrival year into the U.S. Immigrants with no more than 10 years since immigration are classified as “recent immigrants,” and immigrants with more than 10 years are classified as “established immigrants.” We partition immigrants’ English proficiency based on respondents’ self-reported assessment collected by the ACS. We consider three English fluency groups: cannot speak (no English), speaks but not well (some English), and speaks well (fluent English). Finally, we partition the level of economic development of the immigrants’ home country (i.e., country of origin) by combining information on respondents’ country of birth collected by the ACS with data on each country’s gross national income (GNI) per capita for 2019 from the World Bank. Using the threshold levels of GNI per capita (in U.S. dollars) that the World Bank uses to categorize countries into income groups, we divide countries into three groups: low-income, middle-income, and high-income countries.

Thus, we consider an economy with 19 individual types ( $I = 19$ ). One type for natives and 18 types for immigrants partitioned along the aforementioned dimensions: 2 (time since immigration)  $\times$  3 (English fluency)  $\times$  3 (country-of-origin income).

**Individual subtypes.** We then further partition each individual type  $i = 1, \dots, I$  into  $G$  subtypes based on their level of education, age, and gender. Subtypes are indexed by  $g = 1, \dots, G$ . We classify individuals by gender into two groups: male and female. We classify individuals by education into four groups: less than high school degree, high school degree, some college but no degree, and college degree and above. For age, we consider three groups: 25–34, 35–44, and 45–54. As a result, we partition individuals of each type  $i = 1, \dots, I$  into 24 subtypes ( $G = 24$ ) along the aforementioned dimensions: 2 (gender)  $\times$  4 (education)  $\times$  3 (age).

Then, our partition of individuals into types and subtypes implies that individuals observed in the data are classified into one of a total of 456 worker (type, subtype) pairs.

**Market vs. non-market occupations.** We allocate individuals between non-market ( $j = 0$ ) and market ( $j = 1, \dots, J$ ) occupations. We classify an individual as being in the non-market occupation if the individual is not employed or employed but usually works less than 10 hours per week. An employed individual who usually works more than 10 hours per week is assigned to one of the market occupations defined below.

---

<sup>4</sup>Specifically, the group of immigrants includes naturalized citizens and non-citizens. However, we classify natives’ foreign-born children as natives.

**Market occupations.** Our grouping of market occupations follows the two-digit 2010 Standard Occupational Classification (SOC) system, as collected by the ACS. In particular, we consider 25 occupation groups ( $J = 25$ ). Table A1 provides a list of these occupations.

We argue that accounting for rich heterogeneity in worker groups and occupations is important for quantifying the wedges and productivities of immigrants relative to natives as well as the aggregate gains from removing immigrant wedges. As we will show in Section 4, estimated immigrant wedges and productivities across occupations differ substantially across immigrant types and subtypes. Then, in Section 8, we show that ignoring salient dimensions of heterogeneity across immigrants or limiting the granularity of differences in market occupations significantly understates the aggregate gains from removing immigrant wedges.

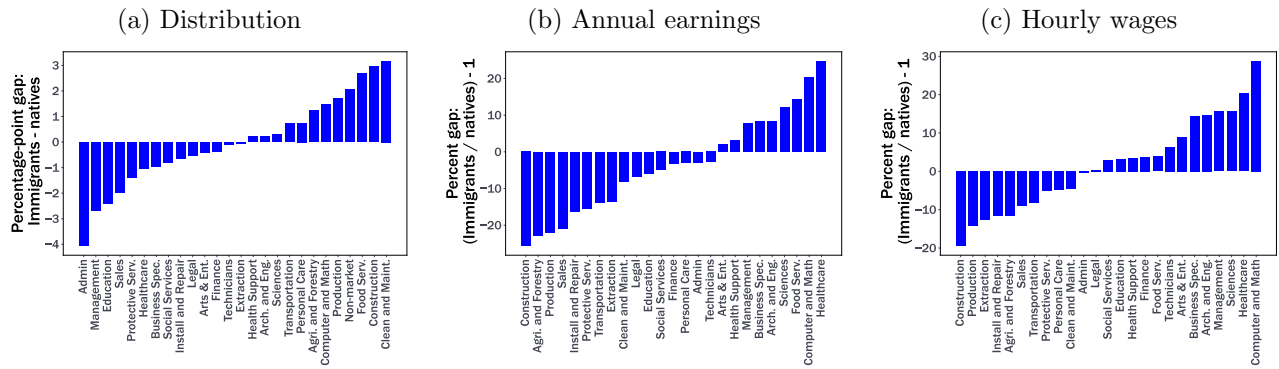
**Annual earnings and hourly wages.** We measure the annual earnings as total annual labor income (in 2019 dollars). We also measure hourly wages of individuals as the ratio of annual earnings to total annual hours worked. For each set of individuals of type  $i$  and subtype  $g$  in market occupation  $j$ , we compute the group’s average annual earnings and average hourly wages as a geometric average among employed individuals with non-missing labor earnings information.

**Summary statistics.** Figure 1 summarizes the distribution, annual earnings, and hourly wages of immigrants across occupations relative to natives in our data. First, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives). Panel (a) presents the percentage-points (pp) gap (calculated as immigrants – natives) between the fractions of immigrants and natives in each occupation. We find that immigrants are more likely to be employed in manual occupations, such as cleaning and maintenance, construction, and services than natives. Among high-paid occupations, the share of immigrants is 1.5 pp higher than the share of natives in computer and mathematical occupations (e.g., programmers, software developers, statisticians, actuaries), while the share of immigrants is 2.7 pp lower than the share of natives in management. Finally, the share of non-employed individuals (i.e., those in the non-market occupation) is 2.1 pp higher for immigrants than for natives.

Panels (b) and (c) present the percent gap (calculated as immigrants/natives – 1) between annual earnings and hourly wages of immigrants and natives, respectively. Among high-paid occupations such as computer and mathematical occupations, the average annual earnings and hourly wages of immigrants are more than 20 percent higher than natives. In contrast, in finance and legal occupations, the average earnings and wages are more similar between the two groups. On the other hand, in low-paying occupations such as construction, production, and extraction, the average earnings and wages are more than 15 percent lower for immigrants than natives.

While these results suggest systematic differences between natives and immigrants across occupations, they potentially mask interesting heterogeneity in outcomes of immigrant types relative to natives within each occupation. Thus, we next examine the extent to which outcomes

Figure 1: Immigration distribution, earnings, and wages across occupations relative to natives



*Notes:* This figure plots the distribution, annual earnings, and hourly wages of immigrants across occupations relative to those of natives using data from the 2010-2019 ACS. We calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives). Panel (a) shows the percentage-point gap (calculated as immigrants – natives) between fractions of immigrants and natives in each occupation. Panels (b) and (c) shows the percent gap (calculated as immigrants/natives – 1) between annual earnings and hourly wages of immigrants and natives, respectively.

differ across immigrant types. Table 1 presents summary statistics on the distribution, annual earnings, and hourly wages of natives and various immigrant types across occupations. In particular, we first calculate the outcomes for each individual (type, subtype) pair, aggregating across subtypes  $g$ , in each occupation. To simplify the exposition, we report the average moments for natives and immigrant types across four broad occupation categories, where we partition the 25 market occupations into categories based on their skill and task-intensity as in Autor and Dorn (2013): non-routine cognitive, non-routine manual, routine cognitive, and routine manual.

The top panel of Table 1 presents the distribution of individuals across occupations. The first column shows the distribution for natives, while the remaining columns show the analogous distributions across various immigrant types. We observe systematic differences by time since immigration (columns 2 and 3): A larger fraction of recent immigrants are in the non-market occupation compared with established immigrants (34% vs. 26%), and the non-employment gap between immigrants and natives disappears among established immigrants. Similarly, English proficiency and the level of economic development of the origin country also appear to be systematically related to immigrants' occupations: Columns 4 and 5 show that immigrants with higher English proficiency are much more likely to work in cognitive occupations (55% vs 5%) and much less likely to be non-employed (25% vs 44%), while columns 6 and 7 show that immigrants from high-income countries are more likely to work in cognitive occupations than immigrants from low-income countries (55% vs 47%).

The middle and bottom panels of Table 1 present the average annual earnings and hourly wages across immigrant types and natives.<sup>5</sup> Our results reveal significant heterogeneity in earn-

<sup>5</sup>Earnings and hourly wages are expressed relative to their respective values for the base native subtype and occupation: native males age 25 to 34 without a high school degree and employed in management, business, science, and arts occupations.

Table 1: Empirical moments

Occupation type	Distribution						
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>
Non-routine cognitive	0.31	0.24	0.24	0.01	0.32	0.35	0.41
Non-routine manual	0.11	0.16	0.16	0.19	0.14	0.14	0.08
Routine cognitive	0.17	0.09	0.12	0.04	0.13	0.12	0.14
Routine manual	0.15	0.18	0.22	0.32	0.16	0.13	0.09
Non-market	0.26	0.34	0.26	0.44	0.25	0.26	0.28
Occupation type	Annual earnings						
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>
Non-routine cognitive	1.78	1.82	2.13	1.14	2.06	2.14	2.31
Non-routine manual	0.76	0.52	0.66	0.46	0.68	0.63	0.77
Routine cognitive	1.04	0.76	0.98	0.58	0.97	0.90	1.22
Routine manual	1.08	0.68	0.89	0.58	0.95	0.87	1.22
Occupation type	Hourly wages						
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>
Non-routine cognitive	1.72	1.94	2.12	1.50	2.09	2.17	2.28
Non-routine manual	0.87	0.71	0.78	0.63	0.81	0.78	0.93
Routine cognitive	1.09	0.96	1.07	0.81	1.08	1.05	1.32
Routine manual	1.08	0.82	0.95	0.75	1.00	0.96	1.25

*Notes:* This table presents the distribution of individuals across market and non-market occupations and their associated annual earnings and hourly wages using data from the 2010-2019 ACS. We first calculate the outcomes for each individual (type, subtype) pair in each 25 occupation. For expositional purposes, we report the average moments for natives and immigrant types across four broad occupation categories, where we assign 25 market occupations into categories based on their skill and task-intensity: non-routine cognitive, non-routine manual, routine cognitive, and routine manual. The distribution of individuals across occupations is conditional on each worker type. Annual earnings and hourly wages are expressed relative to respective values for the base native subtype and occupation: native males of ages 25 to 34 without high school degree and employed in management, business, science, and arts occupations.  $N$  denotes natives,  $I_{0-10}$  denotes recent immigrants ( $\leq 10$  years),  $I_{10+}$  denotes established immigrants ( $>10$  years),  $I_{Low Eng}$  denotes low English proficiency immigrants,  $I_{High Eng}$  denotes high English proficiency immigrants,  $I_{LIC}$  denotes immigrants originating from low-income countries, and  $I_{HIC}$  denotes immigrants originating from high-income countries.

ings and wages across individuals and occupations. We find that immigrants from low-income countries earn less than natives in all occupation groups except non-routine cognitive ones. In contrast, immigrants from high-income countries earn more than natives in all occupations. We also find that immigrants who have been in the country longer, speak English better, and originate from economically developed countries earn more on average across all occupation groups.

The observations above show that immigrants differ systematically from their native counterparts in their occupations as well as in their average earnings and wages in these occupations. To what extent are these differences in the labor market outcomes of immigrants accounted for by differences in their productivities or by frictions faced by immigrants in the U.S. (e.g., immigrant compensation and labor supply wedges)? We investigate this in the following sections.

Table 2: Estimation approach: Parameters and targets

<b>Predetermined parameters</b>			
Parameter	Value	Description	
$\xi$	0.75	Frisch elasticity	
$\{\eta_i\}_{i=1}^I$	4	Frechet shape	
$\sigma$	20	Elasticity across sectoral goods	
$\{\sigma_j\}_{j=1}^J$	20	Elasticity across worker bundles between natives and immigrants	
$\{\tilde{\sigma}_j\}_{j=1}^J$	40	Elasticity across worker bundles between individual types and subtypes	
<b>Estimated parameters</b>			
Parameter	# of parameters	Description	Normalization
$\{z_{ig}^j\}$	11,855	Individual productivity	$z_{bm}^0 = 1$
$\{\tau_g^j\}$	575	Compensation wedges	$\tau_m^j = 0 \forall j, \tau_g^0 = 0 \forall g$
$\{\kappa_{ig}^j\}$	10,800	Immigrant compensation wedges	$\kappa_{1g}^j = 0 \forall g, j, \kappa_{ig}^0 = 0 \forall i, g$
$\{\nu_g^j\}$	600	Preferences	$\nu_g^0 = 1 \forall g$
$\{\gamma_{ig}^j\}$	10,800	Immigrant labor supply wedges	$\gamma_{1g}^j = 0 \forall g, j, \gamma_{ig}^0 = 0 \forall i, g$
$\{N_{ig}\}$	455	Mass of individuals	$\sum_{i,g} N_{ig} = 1$
$\{A_j\}$	25	Occupation productivity	$A_1 = 1$
Total	35,110		
<b>Target moments</b>			
Moment		# of moments	
Share of individuals $(i, g)$ that work in occupation $j \forall i, g, j$		11,855	
Avg. annual earnings of $(i, g)$ in $j$ relative to $(b, m)$ in occupation 1 $\forall i, g, j$		11,855	
Avg. hourly wage of $(i, g)$ in $j$ relative to $(b, m)$ in occupation 1 $\forall i, g, j$		11,400	
Total		35,110	

*Notes:* Individuals of type  $b$  and subtype  $m$  are defined as the base group relative to which various parameters are normalized. See the text for further details.

## 3.2 Estimation approach

We now present our approach to estimating the parameters of the model. The parameter space is partitioned into two groups. The first is predetermined and set to standard values from the literature. The second is estimated to match salient features of the data. Table 2 summarizes our estimation approach, listing the predetermined and estimated parameters and the moments used to pin down the latter.

The set of predetermined parameters consists of  $\xi$ ,  $\{\eta_i\}_{i=1}^I$ ,  $\sigma$ ,  $\{\sigma_j\}_{j=1}^J$ , and  $\{\tilde{\sigma}_j\}_{j=1}^J$ . We set the Frisch elasticity  $\xi = 0.75$ . As discussed in Section 2, the shape parameter  $\eta_i$  of the Frechet distribution of idiosyncratic productivities may vary across types to capture potential



productivity differences across natives and immigrants due to unobserved heterogeneity and immigrant selection. To discipline  $\eta_i$ , we use recent evidence from [Martellini, Schoellman, and Sockin \(2023\)](#) on the average human capital of emigrants, immigrants, and non-migrants across countries. In Figure 4 of their paper (reproduced in Figure A5 for ease of reference), they show that emigrants are more positively selected when migrating from less-developed economies (Panel a). Thus, despite significant differences in the quality of education between rich and poor countries, the average human capital of immigrants in destination countries is close to that of natives (Panel b). Motivated by these findings, and given that we do not model migration decisions, we assume that the idiosyncratic productivity of natives and immigrants is drawn from a common Frechet distribution with shape  $\eta$ —we set this value to 4, as in [Hsieh et al. \(2019\)](#). Importantly, while we think that this assumption is the empirically relevant case given the result in [Martellini, Schoellman, and Sockin \(2023\)](#), we recompute our main results in Section 8 when we instead assume that immigrants and natives are different in their underlying productivities.

We set  $\sigma_j = \sigma \ \forall j = 1, \dots, J$  to simplify the estimation, as it allows us to analytically back out the model’s parameters given the target moments. We set the elasticity of substitution between natives and immigrants to 20 following [Ottaviano and Peri \(2012\)](#).<sup>6</sup> In Section 5.1 we show that the model implies key microeconomic elasticities that are consistent with previous estimates from the literature, lending support for the degree of substitutability across workers of various types implied by our parameterization. In addition, we approximate perfect substitution in the inner nest across labor bundles within natives and immigrants by setting  $\tilde{\sigma}_j = 40 \ \forall j = 1, \dots, J$ .

Our first step to pinning down the estimated parameters is to make a set of normalizations and identifying assumptions. We define an individual base (type, subtype) pair as indexed by  $b \in \{1, \dots, I\}$  and  $m \in \{1, \dots, G\}$ , respectively. Our first normalization consists of setting  $z_{bm}^0 = 1$ . This implies that the productivity of all other individuals is expressed relative to the productivity of the base (type, subtype)  $(b, m)$  in the non-market occupation. Second, we assume that individuals of all types and subtypes face no compensation wedges in the non-market occupation:  $\tau_g^0 = 0$  and  $\kappa_{ig}^0 = 0 \ \forall i, g$ . We also assume that natives that belong to base type and subtype  $(b, m)$  face no compensation wedges in any of the market occupations:  $\tau_m^j = 0 \ \forall j$ . Third, we normalize the preference for the non-market occupation such that  $\nu_g^0 = 1 \ \forall g$ . Fourth, we set immigrant labor supply wedges to zero in the non-market occupation:  $\gamma_{ig}^0 = 0 \ \forall i, g$ . Fifth, we normalize the total mass  $N$  of all individuals to be 1 and the productivity of the first market occupation (management)  $A_1$  to be 1. Finally, as defined in Section 2, we set immigrant compensation and labor supply wedges to zero for natives:  $\gamma_{1g}^j = 0 \ \forall g, j$  and  $\kappa_{1g}^j = 0 \ \forall g, j$ .

We use the remaining parameters to target the share of individuals (type, subtype)  $(i, g)$  in occupation  $j \ \forall i, g, j$ , the average annual earnings of individuals (type, subtype)  $(i, g)$  in occupa-

---

<sup>6</sup>Their preferred estimate of this elasticity is 20 when the native-immigrant elasticity is restricted to be the same for all education groups. In Appendix E, we also present our main results when labor bundles between natives and all immigrants are less substitutable as in [Burstein et al. \(2020\)](#) or perfectly substitutable.

tion  $j$  relative to the average annual earnings of the base (type, subtype)  $(b, m)$  in occupation  $j = 1$ , and the average hourly wages of individuals (type, subtype)  $(i, g)$  in occupation  $j$  relative to the average hourly wages of the base (type, subtype)  $(b, m)$  in occupation  $j = 1$ .<sup>7</sup> In our analysis, we set the base (type, subtype) to be native males age 35 to 44 with a college degree.

### 3.3 Identification

Given the predetermined parameters, normalizations, and target moments, we back out the remaining parameters directly from the data. Our goals in this section are to describe our approach and investigate the features of the data that pin down each parameter. For analytical tractability, we focus on the case of perfect substitution across individuals in the inner nest:  $\tilde{\sigma}_j = \infty \forall j = 1, \dots, J$ . Appendix C provides derivations of the equations used in this section and details about our estimation strategy.

Overall, our methodology follows the approach in Hsieh et al. (2019). In their setup, for example, when two groups of workers share the same productivity distribution and the same distribution of preferences over occupations, we must observe an identical distribution of the two groups across occupations in the data. Thus, if one group is less likely to be observed in an occupation and wages are the same, then it must mean that this group faces barriers in that occupation. Similarly, if these groups are equally likely to be observed in an occupation yet wages are lower for one group, then it must also mean that this group observes barriers in that occupation.<sup>8</sup> As will be shown below, a similar logic applies in our context once we assume that idiosyncratic productivities of natives and immigrants are drawn from a common distribution, as discussed previously. Importantly, we also provide our main results in Section 8 where we instead assume that underlying productivities are different for immigrants and natives.

**Population mass.** We choose the mass of individuals  $N_{ig}$  of each type and subtype  $(i, g)$  to match the respective fraction of individuals observed in the data with such characteristics. In the model, recall that the shares of individuals of each type and subtype  $(i, g)$  is exogenous. Thus, for each  $(i, g)$  pair, we directly set:

$$N_{ig} = \text{Fraction of individuals of type and subtype } (i, g).$$

---

<sup>7</sup>As shown in Table 2, we have more moments for annual earnings than hourly wages since hourly wages are identical for all individuals in the non-market occupation given the linear production technology in this occupation. We set the hourly wage in this occupation in the model to be a fraction  $\lambda$  of weighted average of hourly wages across all market occupations in the data. Similarly, for each (type, subtype) pair, we set annual earnings in the non-market occupation in the model to be a  $\lambda$  of the weighted average of annual earnings across all market occupations in the data. In particular, we set  $\lambda = 0.50$ , which falls within the range of estimated replacement rates provided by unemployment insurance in the U.S. In Appendix E, we provide our main results under alternative values of  $\lambda$ .

<sup>8</sup>Note that, in our context, the imperfect substitution of labor supply between natives and immigrants will also affect identification of wedges, as we will discuss below.

**Preferences and immigrant labor supply wedges.** The solution of the model implies:

$$\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{ig}^k} = \frac{\nu_g^k}{\nu_g^j} \times \frac{1 + \gamma_{ig}^k}{1 + \gamma_{ig}^j}, \quad (1)$$

where  $\text{Earnings}_{ig}^j$  is given by the geometric average annual earnings across all individuals of type and subtype  $(i, g)$  in occupation  $j$ . In the model, the earnings of an individual are given by the right-hand side of its budget constraint.

Given that immigrant labor supply wedges are zero for natives (i.e.,  $\gamma_{1g}^j = 0 \forall g, j$ ) and that the preference for the non-market occupation is normalized to 1 (i.e.,  $\nu_g^0 = 1 \forall g$ ), writing Equation (1) for occupation  $j$  and setting  $k = 0$ , we have the following:

$$\nu_g^j = \lambda \left( \frac{\text{Earnings}_{1g}^j}{\text{Avg. market earnings}_{1g}} \right)^{-1},$$

where  $i = 1$  denotes natives, and  $\text{Avg. market earnings}_{ig}$  denotes the weighted average of  $\text{Earnings}_{ig}^j$  across market occupations  $j$ , with weights given by the share of individuals of such type and subtype that choose each market occupation.<sup>9</sup> That is, the earnings of natives of subtype  $g$  in an occupation  $j$  relative to their weighted average earnings across all occupations is informative about their preference for occupation  $j$ . Using data on natives' earnings in each occupation  $j$  for each subtype  $g$  and data on natives' average market earnings for each subtype  $g$ , this relationship allows us to obtain common preferences  $\nu_g^j \forall g, j$ .

Given preferences  $\{\nu_g^j\}_{g,j}$  and our normalization that the non-market occupation is not subject to immigrant labor supply wedges (i.e.,  $\gamma_{ig}^0 = 0 \forall i, g$ ), we can use Equation (1) to back out these wedges for every immigrant type and subtype  $(i, g)$  in market occupation  $j$  as follows:

$$1 + \gamma_{ig}^j = \lambda \left( \nu_g^j \frac{\text{Earnings}_{ig}^j}{\text{Avg. market earnings}_{ig}} \right)^{-1} = \left[ \left( \frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{1g}^j} \right) / \left( \frac{\text{Avg. market earnings}_{ig}}{\text{Avg. market earnings}_{1g}} \right) \right]^{-1}.$$

Immigrant labor supply wedges are identified by comparing the earnings of immigrants of type  $(i, g)$  in occupation  $j$  relative to their average earnings across occupations vis-a-vis the earnings of natives of subtype  $g$  in occupation  $j$  relative to their average earnings. Thus, given data on the earnings of immigrants and natives for each (type, subtype) pair for each occupation and their average earnings across occupations, we can back out immigrant labor supply wedges  $\gamma_{ig}^j \forall i, g, j$ .

For instance, consider immigrants ( $i > 1$ ) and natives ( $i = 1$ ) of the same subtype  $g$ . Suppose that the average earnings across market occupations are higher for immigrants  $(i, g)$  than for natives  $(1, g)$ . Suppose further that the average earnings for immigrants  $(i, g)$  are *even* larger than that for natives  $(1, g)$  in occupation  $j$ . In this case, the model attributes a lower immigrant

---

<sup>9</sup>Recall from Section 3.2 that, for each (type, subtype) pair, we set the annual earnings in the non-market occupation to be a fraction  $\lambda$  of the weighted average of annual earnings across all market occupations. This implies that  $\text{Earnings}_{ig}^0 = \lambda \times \text{Avg. market earnings}_{ig} \forall i, g$ .

labor supply wedge to this occupation. That is, compared to a scenario where the earnings gap specific to occupation  $j$  is equal to the average earnings gap, immigrants  $(i, g)$  receive lower utility from working in occupation  $j$  and thus need to be compensated with a larger positive earnings gap relative to natives in this occupation.

**Individual productivity: Non-market occupation.** Consider individual (type, subtype) pair  $(i, g)$  in the non-market occupation. The solution of the model implies that:

$$z_{ig}^0 = \left( \frac{\text{Avg. market earnings}_{ig}}{\text{Avg. market earnings}_{bm}} \right)^{\frac{1}{1+\xi}} \left( \frac{\text{Fraction of non-employed}_{ig}}{\text{Fraction of non-employed}_{bm}} \right)^{\frac{1}{\eta}}, \quad (2)$$

where  $(b, m)$  denotes base type-subtype. Then, we have that the productivity of worker type-subtype  $(i, g)$  in the non-market occupation is identified from differences in average market earnings and the fraction of non-employed, relative to the base group. Thus, given data on the fraction of individual (type, subtype) pairs in the non-market occupation and their average market earnings, we obtain their individual productivities in the non-market occupation  $z_{ig}^0 \forall i, g$ .

Consider individuals of type-subtype  $(i, g)$  and  $(b, m)$ . First, assume for a moment that both groups have the same fraction of non-employed individuals. If the former group has higher average market earnings than the latter group, then it must be that the former group has higher productivity at the non-market occupation. Second, assume instead that both groups have the same average market earnings but the fraction of non-employed is higher in the former group: As before, it must be that the former group has higher productivity at the non-market occupation.

**Individual productivity: Market occupations.** Consider individual (type, subtype) pair  $(i, g)$  and some occupation  $j$ . The solution of the model implies that:

$$\frac{z_{ig}^j}{z_{ig}^0} = \frac{\text{Earnings}_{ig}^j / \text{Wages}_{ig}^j}{\text{Earnings}_{ig}^0 / \text{Wages}_{ig}^0} \times \left( \frac{p_{ig}^j}{p_{ig}^0} \right)^{\frac{1}{\eta}}, \quad (3)$$

where  $p_{ig}^j$  denotes the fraction of individuals of type  $(i, g)$  that work in occupation  $j$ , and  $\text{Wages}_{ig}^j$  is given by the geometric average of hourly wages across all individuals of type-subtype  $(i, g)$  in occupation  $j$ . In the model, the wage of an individual is given by  $(1 - \tau_{ig}^j - \kappa_{ig}^j)w_{ig}^j$ . Then, we have that the productivities of individuals across market occupations are identified from differences in the ratio of earnings to wages between market occupation  $j$  and the non-market occupation, as well as from the fraction of individuals employed in occupation  $j$  relative to the non-market occupation. As a result, we obtain their individual productivities  $z_{ig}^j \forall i, g$  across market occupations  $j = 1, \dots, J$ .

The model implies that individuals are estimated to be more productive in market occupation  $j$  relative to the non-market occupation if their earnings-to-wage ratio in occupation  $j$  is higher or if a higher fraction of individuals chooses occupation  $j$  than the non-market occupation.

**Compensation wedges.** We back out common compensation wedges  $\{\tau_g^j\}$  by focusing on natives. Consider natives ( $i = 1$ ) of subtypes  $g$  and  $m$  (base subtype). Then, we have that:

$$1 - \tau_g^j = \frac{\text{Wages}_{1g}^j}{\text{Wages}_{1m}^j}.$$

Thus, given data on wages of native (type, subtype) pairs across occupations, we can obtain common compensation wedges  $\tau_g^j \forall g, j$ . This expression implies that the common compensation wedges  $\tau$  that apply to all natives and immigrants in an occupation  $j$  are identified from data on the wages of natives relative to those of the base subtype for the given occupation. In particular, natives of subtype  $g$  whose wages in occupation  $j$  relative to those of the base subtype are lower are inferred to have positive compensation wedges.

We now proceed to back out immigrant compensation wedges  $\{\kappa_{ig}^j\}$ . Let  $(i, g)$  denote an immigrant of a given type-subtype, and let  $(1, g)$  denote her native counterpart. Then, the solution of the model implies:

$$\frac{1 - \tau_g^j - \kappa_{ig}^j}{1 - \tau_g^j} = \frac{\text{Wages}_{ig}^j}{\text{Wages}_{1g}^j} \left\{ \frac{\sum_{q \in \mathcal{I}_i} \sum_{r=1}^G N_{qr} (z_{qr}^j)^{1+\xi} [(1 + \gamma_{qr}^j) \nu_r^j \text{Wages}_{qr}^j]^\xi (p_{qr}^j)^{\frac{\eta-(1+\xi)}{\eta}}}{\sum_{r=1}^G N_{1r} (z_{1r}^j)^{1+\xi} [(1 + \gamma_{1r}^j) \nu_r^j \text{Wages}_{1r}^j]^\xi (p_{1r}^j)^{\frac{\eta-(1+\xi)}{\eta}}} \right\}^{\frac{1}{\sigma_j}}. \quad (4)$$

where  $\mathcal{I}_i$  is the set of immigrant types. Then, using data on wages and allocations across (type, subtype) pairs, as well as the rest of the parameters estimated thus far, we can obtain immigrant compensation wedges  $\kappa_{ig}^j \forall i, g, j$ .

This first term implies that immigrant compensation wedges are identified by using similar information used to back out common compensation wedges. Any under-compensation in wages relative to their native counterparts is interpreted as positive immigrant compensation wedges.

Additionally, the second term of the right-hand side arises from the imperfect substitutability between natives and immigrants. The numerator can be thought of as a measure of aggregate labor supply of *all* immigrants, which is proportional to population as well as occupation-specific productivity, hours worked, and allocations. On the other hand, the denominator is the same for *all* natives. This term implies that differences in the relative supply between natives and immigrants are also captured by immigrant compensation wedges. For instance, if immigrants are a small fraction of the population but have similar productivities in occupation  $j$ , work similar hours, and are observed to be equally likely as natives to choose this occupation, then immigrant compensation wedges  $\kappa$  in this occupation would be positive. For  $\kappa$  to be zero, immigrants would need to be paid relatively more than natives given their relative scarcity.

**Occupation productivity.** Consider the base type and subtype  $(b, m)$ , along with two alternative market occupations  $j$  and  $k$ . Let  $k$  be given by the first occupation such that  $A_k = 1$  given our normalizations. The solution of the model implies that:

$$A_j = \left\{ \frac{\left( \frac{\text{Wages}_{bm}^j}{\text{Wages}_{bm}^1} \right)^\sigma \sum_{g=1}^G N_{bg} (z_{bg}^j)^{1+\xi} [\nu_g^j \text{Wages}_{bg}^j]^\xi (p_{bg}^j)^{\frac{\eta-1}{\eta}}}{\sum_{g=1}^G N_{bg} (z_{bg}^1)^{1+\xi} [\nu_g^1 \text{Wages}_{bg}^1]^\xi (p_{bg}^1)^{\frac{\eta-1}{\eta}}} \right\}^{\frac{1}{\sigma-1}}. \quad (5)$$

Note that all objects in this expression can be computed either directly from the data or indirectly using data along with the derivations above. Thus, Equation (5) allows us to obtain occupation productivities  $A_j \forall j$ .

This expression contrasts the relative labor supply of the base type  $b$  between occupation  $j$  and the base occupation ( $j = 1$ ). Controlling for differences in wages of the base (type, subtype) across occupations, if labor supply of the base type is higher in an occupation  $j$  relative to that in the base occupation, then occupation  $j$  is inferred to feature higher occupational productivity.

## 4 Immigrant Wedges: Estimates and Impact

In this section, we study the extent and implications of immigrant wedges in the U.S. In Section 4.1, we begin by estimating the parameters of the model following the approach described in the previous section.<sup>10</sup> Next, in Sections 4.2 and 4.3, we analyze the macroeconomic effects of eliminating the immigrant wedges, both in the aggregate and across the distribution.

### 4.1 Estimates of immigrant wedges and productivities

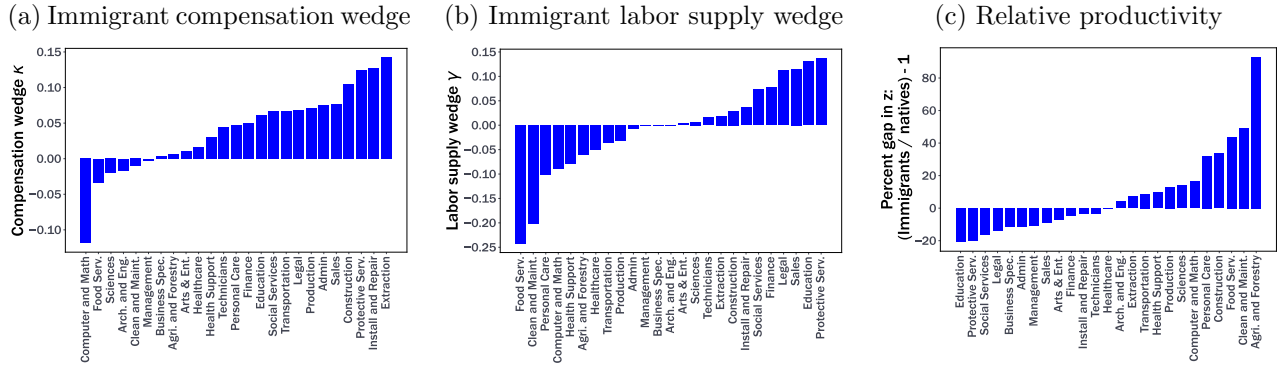
We begin by presenting our estimates of immigrant wedges ( $\kappa$  and  $\gamma$ ) and productivity ( $z$ ) in the U.S. Figure 2 presents averages across market occupations, and Table 3 presents averages across immigrant types. Heterogeneity in the estimated wedges can shed light on the mechanisms underlying them, while also serving to externally validate the reasonability of our estimates. Given the large number of parameters of our model (35110 parameters, as described in Table 2), we restrict attention to weighted averages of the estimated parameters wherever necessary. Table A2 shows that the model closely matches the distribution of individuals across occupations as well as their associated annual earnings and hourly wages in the data shown in Table 1.

**Immigrant wedges and productivities across occupations.** Panel (a) in Figure 2 shows that immigrant compensation wedges vary significantly across occupations. For instance, these wedges are estimated to be largest typically in manual occupations such as extraction, installation, maintenance, and repair, and protective services, and lowest in non-routine cognitive occupations such as sciences, architecture and engineering, management, and healthcare. Two exceptions are noteworthy. First, legal services stands out as a non-routine cognitive occupation with high immigrant compensation wedges. Second, computer and mathematical occupations

---

<sup>10</sup>Recall that our estimation approach is derived under the restriction that there is perfect substitution across labor bundles in the inner nest. Thus, we estimate the parameters under this restriction with  $\tilde{\sigma}_j = 40 \forall j = 1, \dots, J$  to approximate an economy with perfect substitution across labor bundles in the inner nest. Appendix E also presents our main results under an even higher value of  $\tilde{\sigma}_j$  to approximate perfect substitution.

Figure 2: Average immigrant compensation and labor supply wedges and relative productivities



Notes: This figure plots the average values of immigrant compensation  $\kappa$  and labor supply  $\gamma$  wedges as well as the percent gap in productivity  $z$  between immigrants and natives (calculated as immigrants/natives - 1) across market occupations.

observe large immigrant compensation subsidies (i.e., negative compensation wedges).

Panel (b) shows that in about half of the occupations, immigrant labor supply wedges are negative, implying that working in these occupations is less attractive to immigrants than to natives. For instance, among cognitive occupations, computer, mathematical, and healthcare roles have negative immigrant labor supply wedges, while finance and legal jobs have positive ones. Among manual jobs, food, cleaning, and personal care services have large negative wedges, while protective services and installation, maintenance, and repair jobs have positive ones.

Finally, Panel (c) presents the percent gap in productivity  $z$  between immigrants and natives (calculated as immigrants/natives - 1) across market occupations. Among cognitive occupations, immigrants are more productive in computer and math fields, just as productive in healthcare and finance, but less productive in legal occupations. On the other hand, among manual occupations, immigrants are estimated to be more productive than natives in agriculture, construction, production, transportation, and services (food services, cleaning, and personal care occupations).

These estimates show that there are significant differences in immigrant barriers and relative productivities across occupations. For instance, immigrants are typically more productive than natives in manual occupations, but they also face substantial barriers in these occupations. As such, we argue that working with a model that accounts for the heterogeneous outcomes of immigrants across occupations is critical for understanding the aggregate and distributional implications of immigrant barriers.

**Immigrant wedges and productivities across immigrant types.** We now examine the extent to which immigrant wedges and productivities differ across immigrant types. Table 3 reports weighted averages of immigrant compensation wedges  $\kappa_{ig}^j$ , immigrant labor supply wedges  $\gamma_{ig}^j$ , and individual productivities  $z_{ig}^j$ . While we focus our discussion on immigrant wedges and individual productivities, we also report estimates of common compensation wedges  $\tau_g^j$ , common preference shifters  $\nu_g^j$ , and occupation productivities  $A_j$ .

Table 3: Estimation results

Occupation type	Immigrant compensation wedge $\kappa$							Common
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>	comp. wedge $\tau$
Non-routine cognitive	0.00	0.02	-0.01	0.01	-0.01	0.00	-0.06	0.25
Non-routine manual	0.00	0.02	-0.01	0.03	-0.01	0.03	-0.05	0.32
Routine cognitive	0.00	0.11	0.06	0.08	0.07	0.11	0.02	0.38
Routine manual	0.00	0.12	0.07	0.10	0.06	0.09	-0.02	0.28
Non-market	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Occupation type	Immigrant labor supply wedge $\gamma$							Common
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>	pref. $\nu_g^j$
Non-routine cognitive	0.00	0.01	0.00	-0.07	0.01	0.02	0.03	0.46
Non-routine manual	0.00	-0.18	-0.17	-0.26	-0.12	-0.09	-0.03	0.78
Routine cognitive	0.00	0.10	0.03	-0.08	0.07	0.17	0.06	0.57
Routine manual	0.00	0.01	-0.02	-0.05	0.02	0.02	0.07	0.54
Non-market	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Occupation type	Worker productivity $z$							Occupation
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>	prod. $A$
Non-routine cognitive	0.63	0.60	0.59	0.58	0.59	0.61	0.58	0.87
Non-routine manual	0.52	0.69	0.68	0.78	0.62	0.63	0.52	0.41
Routine cognitive	0.76	0.62	0.70	0.59	0.68	0.64	0.65	0.67
Routine manual	0.70	0.79	0.82	0.86	0.75	0.75	0.67	0.53
Non-market	0.82	0.77	0.76	0.61	0.84	0.84	0.96	0.25

*Notes:* This table presents estimated common compensation wedges  $\tau$ , immigrant compensation wedges  $\kappa$ , common preference shifter  $\nu$ , immigrant labor supply wedges  $\gamma$ , individual productivity  $z$ , and occupation productivity  $A$ . For expositional purposes, we report these outcomes across four broad occupation categories, where we assign 25 market occupations into categories based on their skill and task-intensity: non-routine cognitive, non-routine manual, routine cognitive, and routine manual.

We find systematic differences in immigrant barriers and productivities by time since immigration. Recent immigrants face larger compensation wedges across all occupations compared with established immigrants. This pattern aligns with previous research (e.g., [Dostie, Li, Card, and Parent 2020](#)), indicating a period of adjustment and integration for new immigrants. We also find that recent immigrants are less productive in routine occupations but slightly more productive in non-routine occupations than established immigrants.

Next, estimates also imply noticeable differences in immigrant barriers and productivity based on English proficiency. Immigrants with lower English skills have higher compensation wedges in all occupations. Additionally, these individuals have negative labor supply wedges, with the magnitude of these wedges varying significantly across occupations. Immigrants with lower English proficiency are also less productive in cognitive roles than natives, yet more productive than natives in manual occupations.



Finally, we find that an immigrant’s country of origin also correlates with their labor market outcomes. Immigrants from high-income countries face minimal or negative compensation wedges in many occupations. In contrast, those from low-income countries experience much higher compensation wedges, particularly in routine occupations. Furthermore, immigrants from low-income countries are estimated to be more productive than natives in manual occupations.

Overall, recent immigrants, those from low-income countries, and those with low English proficiency are more productive than natives in manual occupations, but at the same time, these immigrant types also observe the largest immigrant barriers in these occupations. As such, from the lens of our model, despite being more productive in these occupations, immigrant barriers distort their labor market outcomes along two dimensions. First, larger barriers induce immigrants to stay non-employed. Second, differences in immigrant barriers across occupations distort the allocation of employed immigrants across occupations and their hours worked.

## 4.2 Aggregate implications of immigrant wedges

We now investigate the aggregate implications of the immigrant wedges. Our goal is to study how immigrant barriers affect outcomes such as real GDP, total factor productivity (TFP), employment, and average hours worked. To do so, we contrast the outcomes in the baseline model with those implied by a counterfactual economy in which immigrant wedges are removed; i.e.,  $\gamma_{ig}^j = 0$  and  $\kappa_{ig}^j = 0 \forall i, g, j$ . Thus, in the latter, natives and all immigrant types are subject to the same level of distortions across occupations.

**Aggregate real GDP gains.** The first column of Panel A in Table 4 presents the effects of removing immigrant wedges in the aggregate and across broad occupation groups. We find that removing *all* the barriers that immigrants face in the U.S. increases real GDP by 6.98%.<sup>11</sup>

To evaluate the quantitative significance of this finding, we contrast the effects from removing immigrant wedges to the overall contribution of immigrants to the U.S. economy. We compute the contribution of immigrants by comparing the baseline model with a counterfactual economy without immigrants, which we solve by setting the mass of immigrants to zero. Results in Table A3 imply that real GDP is 28.2% higher with immigrants relative to an economy without immigrants (1/0.78). This means that real GDP gains from removing immigrant wedges represent 24.8% of the total gains from immigration itself (6.98/28.2). Hence, existing barriers undermine the overall contribution of immigrants and removing immigrant wedges significantly raises the productive capacity of immigrants.

Next, we investigate the sources underlying these real GDP gains. The output increase is driven by three channels: (*i*) flows of immigrants between the non-market occupation and market

---

<sup>11</sup>When we only remove immigrant compensation wedges but keep immigrant labor supply wedges unchanged at their estimated values, real GDP increases by around 5.9%, implying that most of the gains are attributable to the removal of immigrant compensation wedges.

Table 4: Aggregate and sectoral effects of removing wedges

Occupation type	Percent change				Change in immigrant share (pp)
	Real GDP	TFP	Employment	Hours	
A. Full reallocation					
Aggregate	6.98	2.48	1.91	2.43	1.62
Non-routine cognitive	7.95	4.20	2.61	0.96	2.23
Non-routine manual	14.29	0.77	7.38	5.15	5.10
Routine cognitive	2.79	1.15	0.07	1.52	0.18
Routine manual	5.10	2.42	-1.51	5.89	-1.03
B. Within-market reallocation					
Aggregate	4.99	2.42	0.00	2.50	0.00
Non-routine cognitive	6.28	3.63	1.62	0.92	8.67
Non-routine manual	10.04	1.22	2.81	5.73	7.24
Routine cognitive	1.65	1.11	-1.04	1.59	-6.42
Routine manual	2.39	2.28	-3.98	4.25	-12.32

*Notes:* Panel A presents the percent change in aggregate and occupation-specific real GDP, TFP, employment, and hours when immigrant wedges are set equal to their counterpart natives of the same subtype. Aggregate real GDP is output produced in the market sector, total factor productivity (TFP) is real GDP per hour, employment is the mass of workers in market occupations (or each occupation), and hours is the average hours worked in market occupations (or each occupation). The change in the immigrant share denotes the percentage point (pp) change in the fraction of immigrants employed in market occupations or each occupation. Panel B presents the same results when we prevent inflows to and outflows from the non-market occupation upon removal of immigrant wedges to isolate the effects of within-market reallocation.

occupations, (ii) the reallocation of employed workers across market occupations and resulting change in the distribution of market occupations, and (iii) the change in average hours worked across market occupations. We find that increases in TFP, employment, and hours worked all contribute to the rise in real GDP, with TFP gains having the largest contribution.

To quantify the role of flows of immigrants between the non-market occupation and market occupations, in Panel B of Table 4, we recompute the effects of removing wedges when we prevent individuals from moving in and out of the non-market occupation. We find that around 30% of real GDP gains from removing wedges are due to the movement of individuals in and out of the non-market occupation. On the other hand, the TFP gains from reallocation of already employed workers across market occupations as well as changes in their hours worked contribute almost equally to the remaining real GDP gains.

**Real GDP gains across occupations.** Underlying the aggregate gains, the removal of immigrant wedges have heterogeneous effects across occupations.<sup>12</sup> Real GDP increases in all broad occupation categories, but there are significant quantitative differences between them: Real GDP gains are much larger in non-routine occupations than in routine occupations.

<sup>12</sup>While Table 4 provides GDP gains and sources behind these gains across broad occupation groups, we also repeat this exercise across all 25 market occupations in Figure A6.

In terms of employment changes, routine manual occupations experience a large decrease in employment, while non-routine manual occupations feature a substantial increase when barriers are removed. Restricting worker mobility in and out of the non-market occupation would have led to a more marked decline in employment in routine manual occupations and a lesser growth in non-routine manual occupations. This result suggests that new entrants to market occupations predominantly opt for manual occupations. On the other hand, employment in non-routine cognitive occupations is much less affected from the movement of individuals in and out of the non-market occupation, suggesting that the main reason behind the rise in employment in this occupation is the reallocation of employed workers from other occupations. Similarly, Panel B also indicates that within-market reallocation of employed workers leads to a decline in employment in routine occupations and an increase in employment in non-routine occupations. Overall, these results imply that removal of immigrant wedges reallocates non-employed workers to mainly manual occupations, and employed workers from routine to non-routine occupations.

The greatest TFP gains occur in non-routine cognitive occupations, accounting for more than 50% of real GDP gains in these occupations. In contrast, the TFP contributions to real GDP gains are much smaller in non-routine manual occupations, which observe a significant influx of workers from the non-market occupation. Without this influx, TFP gains in these occupations could have been higher. This is because the workers transitioning from the non-market occupation to non-routine manual occupations are negatively selected productivity-wise relative to the existing pool of employed workers, leading to a minor dilution in overall productivity.

Finally, hours worked increase across all broad occupation groups, but the magnitude of this increase varies. Gains in average hours worked contribute the most to real GDP gains in routine manual occupations, while these gains are the least important in accounting for real GDP gains in non-routine cognitive occupations.

**Reallocation patterns across immigrants.** The results reported in Table 4 show that the reallocation patterns of individuals from the non-market occupation to market occupations as well as between market occupations are relevant in driving real GDP gains both in the aggregate and across occupations. Motivated by these findings, Table 5 presents the distribution of worker reallocation patterns for immigrant type/subtypes. In this table, we consider all four possible types of reallocations: movements from the non-market occupation to market occupations (N-E: Extensive), movements from market occupations to the non-market occupation (E-N: Extensive), switches between market occupations conditional on being employed prior to the removal of wedges (E-E: Intensive), and staying in the same market or non-market occupation (EE/NN: Stayer). For each row representing a type/subtype, we present the share of individuals making a particular type of reallocation—that is, for each row, the four columns sum to one.

Overall, our results show that removing immigrant wedges allows disadvantaged immigrant groups to either reallocate from the non-market occupation to market occupations or to switch

Table 5: Reallocation patterns by immigrant type/subtype

Category	Immigrant type/subtype	N-E: Extensive	E-N: Extensive	E-E: Intensive	EE/NN: Stayer
Age	25-34	0.089	0.013	0.200	0.697
	35-44	0.093	0.009	0.196	0.701
	45-54	0.094	0.005	0.197	0.704
Gender	Male	0.051	0.008	0.245	0.696
	Female	0.132	0.011	0.152	0.705
Education	Less than high school	0.127	0.004	0.216	0.652
	High school	0.115	0.003	0.214	0.667
	Less than college	0.092	0.004	0.187	0.717
	College	0.048	0.021	0.178	0.754
Duration	Recent immigrants	0.128	0.011	0.235	0.626
	Established immigrants	0.077	0.008	0.182	0.733
Country of origin	High-income country	0.071	0.027	0.227	0.675
	Middle-income country	0.106	0.002	0.191	0.701
	Low-income country	0.074	0.016	0.197	0.713
English proficiency	No English	0.219	0.001	0.218	0.563
	Some English	0.162	0.001	0.254	0.583
	Fluent English	0.060	0.012	0.181	0.747

*Notes:* This table presents the distribution of workers that reallocate when immigrant wedges are removed. Four types of reallocation are considered: movements from the non-market occupation to market occupations (N-E: Extensive), movements from market occupations to the non-market occupation (E-N: Extensive), switches between market occupations conditional on being employed prior to the removal of wedges (E-E: Intensive), and staying in the same occupation market or non-market occupation (EE/NN: Stayer). For each row representing a type/subtype, we present the share of individuals making a particular type of reallocation—that is, for each row, the four columns add up to one.

across market occupations depending on their employment status prior to removal of wedges. For instance, we find that immigrants with a high school degree or less are more likely to experience a transition from the non-market occupation to market occupations as well as switches between market occupations compared to immigrants with a college degree. The same is also true for recent immigrants relative to established immigrants, or those with less or some English fluency relative to those who are fluent in English. Furthermore, across gender groups, while the fraction of immigrants staying in their existing occupations is almost the same for male and female immigrants, males are more likely to switch their occupations and females are more likely to enter into market occupations from the non-market occupation.

### 4.3 Distributional implications of immigrant wedges

We now analyze the distributional implications of immigrant barriers. To do so, we compute the impact of removing only the wedges faced by immigrants of some type or subtype—comparing the baseline model with a counterfactual economy identical to the baseline, except that immigrant wedges of the given type or subtype are set to zero. This exercise allows us to shed light on the heterogeneous payoffs associated with the targeted removal of immigrant wedges.

Our findings are reported in Table 6. The first column of the table reports real GDP gains

Table 6: Gains from removing wedges by immigrant type/subtype

Category	Immigrant type/subtype	Real GDP	Share of population	Real GDP growth
		(% change)	(baseline level, %)	per 1% of imm. (%)
Age	25-34	1.76	6.03	0.29
	35-44	3.11	6.97	0.45
	45-54	1.97	5.97	0.33
Gender	Male	3.30	9.22	0.36
	Female	3.53	9.75	0.36
Education	Less than high school	2.88	5.06	0.57
	High school	1.99	4.21	0.47
	Less than college	1.20	3.62	0.33
	College	0.77	6.08	0.13
Duration	Recent immigrants	3.35	5.65	0.59
	Established immigrants	3.47	13.31	0.26
Country of origin	High-income country	0.89	2.49	0.36
	Middle-income country	3.80	11.28	0.34
	Low-income country	2.14	5.20	0.41
English proficiency	No English	0.76	1.52	0.50
	Some English	2.86	3.65	0.78
	Fluent English	3.21	13.79	0.23

*Notes:* This table presents the effect of removing immigrant wedges by immigrant type/subtype on real GDP. The first column presents the percent change in real GDP when immigrant wedges of a given type/subtype are removed—while keeping immigrant wedges unchanged for other immigrant groups—relative to the baseline. The second column presents the share of immigrants of each type/subtype in the total population. Finally, the third column presents the ratio of real GDP growth (column 1) to the share of each immigrant type/subtype in the economy (column 2), to adjust for heterogeneity in the mass of individuals across groups.

from removing the immigrant wedges faced by the immigrant group listed in the rows of the table—while keeping immigrant wedges unchanged for other immigrant groups. Given that the number of immigrants differs across immigrant groups, the third column reports real GDP gains from removing immigrant wedges, controlling for the footprint of each immigrant group. Specifically, we use the share of immigrants that belong to each group (the second column) to express real GDP gains per 1% of immigrants in the total population.

We find significant differences in the effects of removing immigrant wedges across demographic groups. For instance, removing immigrant wedges faced by immigrants without a high school degree increases real GDP by 0.57% per 1% of the population that is an immigrant with less than a high school degree, while the respective value for immigrants with a college degree is 0.13%. The removal of wedges for immigrants without a high school degree results in these immigrants having a much larger outflow from the non-market occupation and a larger degree of reallocation within market occupations compared with those with a college degree, as seen

in Table A4. Across age groups, we find that real GDP gains per immigrant have an inverse U-shaped pattern, with the largest gains for prime-age (35-44) individuals.

We also find that the effects of removing immigrant wedges are heterogeneous across immigrant types. For instance, removing immigrant wedges for recent immigrants and immigrants with some English proficiency leads to the largest real GDP gains per immigrant. While these findings suggest that newcomers face significant barriers, much smaller gains from removing the immigrant wedges of established immigrants and those with strong English proficiency suggest that these barriers decay over time. Across country of origin, we find that real GDP gains per immigrant are highest for wedges removed for immigrants from low-income countries.

These results highlight that real GDP gains per immigrant are heterogeneous across immigrant types and subtypes, with effects largest among recent immigrants, less-educated immigrants, immigrants who are not fluent in English, and immigrants from low-income countries. These findings are accounted for by significant differences in immigrant barriers faced by these groups, as shown in Table 3, despite having higher productivity in certain occupations.<sup>13</sup>

## 5 Immigration Policy Reform

Thus far, we have shown that the barriers immigrants face in the labor market cause substantial output losses in the aggregate and that these losses vary systematically across the occupations and immigrant groups. A natural question that arises is: to what extent do these barriers affect the outcomes of immigration policies that admit new immigrants of varying characteristics? The gains associated with the admission of new immigrants into the U.S. may be subdued in the presence of barriers that prevent their efficient allocation in the labor market.

We now investigate the implications of immigrant barriers on aggregate outcomes associated with a rise in the stock of immigrants. We consider a scenario in which the U.S. chooses to admit more immigrants into the country and ask two questions. First, how do aggregate productivity gains arising from the admission of new immigrants into the U.S. differ across immigrant types? Second, how are the returns to increased immigration affected by immigrant wedges? We interpret the answers to these questions as informative about the potential effects of implementing alternative immigration policies in the U.S., as well as about the extent to which the gains from such policies can be amplified by removing immigrant barriers.

Importantly, the returns to increased immigration fundamentally depend on how admitting new immigrants affects the outcomes of natives and existing immigrants. Thus, before evaluating alternative immigration policies, we first contrast the model's implications for the labor outcomes of natives and existing immigrants following an increase in the stock of immigrants vis-a-vis their empirical counterpart in Section 5.1. Critically, we compute elasticities in the model that are

---

<sup>13</sup>We also investigate heterogeneity in the gains from removing immigrant wedges across occupations. As shown in Table A5, we find that real GDP gains per immigrant are highest when immigrant barriers are removed in non-routine cognitive occupations and lowest when they are removed in non-routine manual occupations.

comparable to empirical estimates obtained from microeconomic studies. This exercise allows us to validate the magnitudes of key elasticities in our model. Next, in Section 5.2, we use our model to answer the aforementioned questions on the effects of alternative immigration policies.

## 5.1 Microeconomic elasticities: Model vs data

To contrast various elasticities in our model with existing estimates in the literature, we begin by discussing the set of empirical studies that we focus on. We then proceed to develop a model experiment that serves as the model-counterpart of these empirical studies. We conclude this subsection by contrasting the model-implied estimates with the empirical estimates.

**Empirical estimates.** To keep this section focused but relevant, we turn to papers that analyze the effects of a widely studied and large-scale immigration shock experienced in the U.S. in 1980. Specifically, between May and September 1980, around 125,000 Cuban immigrants (the *Marielitos*) arrived in Miami after Fidel Castro declared that Cubans wishing to immigrate to the U.S. were free to leave Cuba from the port of Mariel. Several papers (e.g., [Card 1990](#); [Borjas 2017](#); and [Peri and Yasenov 2017](#), among others) measure elasticities of labor market outcomes of various groups to this immigration shock by comparing outcomes in Miami and control cities before and after the arrival of the Marielitos to Miami (the “Marielitos shock”).<sup>14</sup>

The Marielitos increased the labor force of Miami by around 8% at the end of 1980. They were more likely to be young, male, and with less education: Only 18% had a college degree, 55.6% were male, and 38.7% were young (between ages 21 and 30). Empirical studies used this sudden inflow of immigrants as a quasi-natural experiment to measure how immigrants affect the labor market outcomes of natives. [Card \(1990\)](#) first studies this question, comparing changes in the wages and unemployment rates across demographics between 1979 and 1985 in Miami vis-a-vis those in four cities with similar employment growth as Miami. This study concludes that the inflow of immigrants had almost *no* impact on the outcomes of natives in Miami.

[Peri and Yasenov \(2017\)](#) revisit the same experiment and use empirical methods developed over the years since [Card \(1990\)](#). In particular, the choice of control group, i.e., comparison cities, in [Card \(1990\)](#) is based on trends observed after the immigration shock rather than prior to the treatment. [Peri and Yasenov \(2017\)](#) implement a synthetic control method to create a new synthetic city that best resembles the pre-Marielitos labor market in Miami by estimating city weights. In the end, [Peri and Yasenov \(2017\)](#) confirm the early findings of [Card \(1990\)](#), as they find limited changes in the outcomes of native high school dropouts after the immigration shock. On the other hand, different from [Peri and Yasenov \(2017\)](#), [Borjas \(2017\)](#) finds that

---

<sup>14</sup>Focusing on the Marielitos shock has an added advantage, as the effects of this shock are measured using the pure spatial approach, which uses variation in the inflow of immigrants across regions. [Dustmann, Schönberg, and Stuhler \(2016\)](#) argue that this approach identifies the total effect of immigration on labor market outcomes of a particular skill group. Thus, analyzing the total effects through a pure spatial approach provides easily interpretable estimates that are policy relevant.

wages of natives who are high school dropouts in Miami declined significantly after the inflow of the Mariel immigrants, using the March CPS instead of ORG-CPS. [Peri and Yasenov \(2017\)](#) argue that this difference in results is due to small subpopulations of the March CPS that exhibit significant fluctuations in average wages around the long-run trend between 1972 and 1991.

**Model-counterpart to empirical estimates.** While we acknowledge that there is a debate in the literature about the magnitude of empirical estimates—especially because of the small sample size used in these analysis—we still contrast the implications of the model with the empirical estimates documented by these studies for two reasons. First, computing these elasticities in the model allows us to document how an increase in immigration affects labor market outcomes of natives and existing immigrants according to our model. This way, we are able to present reasonableness of our model’s predictions. Second, the comparison of model-implied elasticities with existing empirical estimates helps us to validate our model’s predictions.

We construct a model-counterpart to the Marielitos shock by considering a counterfactual in which new immigrants with similar characteristics as the Marielitos become part of the U.S. economy. We use our model of the U.S. economy as our model of Miami upon the arrival of the Marielitos.<sup>15</sup> Thus, we increase the total mass of new immigrants such that the total population in the model increases by 8%. To match the demographics of the Marielitos, we assume that all new immigrants originate from middle-income countries, given that Cuba was a middle-income country based on our classification in Section 3.1. Furthermore, 82% of the new immigrants have no college degree; 55.6% are male; and 38.7% are classified under the first age group (25-34) while the rest equally divided across the remaining age groups.<sup>16</sup>

**Results.** We solve the model under the Marielitos shock described above and examine its implications for wages and unemployment rates relative to the baseline. First, for each economy, we compute the average of the logarithm of unit wages  $w$ , as well as the level of the unemployment rate (fraction in the non-market occupation) for natives and immigrants. Then, we compute differences in these outcomes between the two economies.

Table 7 reports changes in the labor market outcomes of natives and immigrants upon the inflow of the Marielitos in both the data and the model.<sup>17</sup> The empirical estimates show that

---

<sup>15</sup>Here, we use our model estimated using 2010-2019 ACS data and, thus, with the same parameters and wedges that we document in Section 4.1. Results presented in Table 7 remain similar when we instead re-estimate the model using 1980 ACS data for the entire U.S. or for Florida only.

<sup>16</sup>We do not have information on the fraction of the Marielitos that spoke English and at what level. Thus, we assume that the distribution of the Marielitos immigrants across the three English fluency groups defined in Section 3.1 is the same as the rest of the U.S. immigrant population in our analysis.

<sup>17</sup>We use Table 3, Table 4, and Table 7 in [Card \(1990\)](#) to calculate the change in (i) the logarithm of real hourly wages of white natives in Miami relative to that in comparison cities, (ii) the unemployment rate of white natives in Miami relative to that in comparison cities, and (iii) Cuban immigrant wages in Miami relative to Cuban immigrants in the rest of the U.S. between 1981 and 1982 relative to 1979, respectively. Finally, Table 3 in [Peri and Yasenov \(2017\)](#) provides estimates for the change in the logarithm of real hourly wages for high-school dropouts in Miami relative to the synthetic control city between 1981 and 1982 relative to 1979.



Table 7: Effects of the Mariel immigrants on outcomes of natives and immigrants: Data vs model

Moment	Data	Model
Change in log wages of natives (pp)	0.5	0.3
Change in log wages of less-educated natives (pp)	1.1	0.3
Change in unemployment rate of natives (pp)	-1.7	-0.2
Change in log wages of immigrants (pp)	-4.5	-4.7

*Notes:* This table compares changes in the labor market outcomes of natives and immigrants upon an inflow of immigrants in the data and the model. Empirical estimates are obtained from Card (1990) and Peri and Yasenov (2017), who measure changes in outcomes of natives and previous immigrants after the arrival of Cuban immigrants to Miami in 1980. Using our model, we simulate an analogous inflow of immigrants to obtain model-based estimates. Please refer to the main text for details about this exercise.

the inflow of Mariel immigrants had limited effects on the outcomes of natives but relatively larger effects on the wages of immigrants in Miami.<sup>18</sup> This result is largely consistent with the predictions of our model, as we now describe.

Our model implies limited changes in native labor market outcomes upon the inflow of immigrants to the economy. This implication is largely accounted for by the imperfect substitutability between immigrant and native labor inputs in the production technology. Imperfect substitution limits the degree to which the rise in immigrant labor supply crowds out the native labor supply. In addition, the rise of immigrant labor supply leads to an increase in production and the native labor supply also increases slightly, as evidenced by the decline in the unemployment rate of natives (i.e, the fraction in the non-market occupation). An economy that features perfect substitution between immigrants and natives would imply stronger crowding-out effects of immigrants on natives, potentially leading natives to experience a rise in unemployment. As such, the limited effects of the immigrant shock on native outcomes serves as an external validation for our modeling choice of imperfect substitutability between native and immigrant labor bundles.

On the other hand, our model implies a relatively larger change in the wages of existing immigrants. Two channels account for this prediction. First, as described above, the Mariel immigrants were predominantly less educated. These new immigrants select into low-paid occupations, decreasing the average wages of all immigrants. Second, the production technology in our model features perfect substitutability in the labor supply of different types of immigrants. Thus, an increase in the labor supply of immigrants reduces the average wages of immigrants.

## 5.2 Immigration policy

We now use our model to investigate the potential impact of a broad set of immigration policies. We focus on policies that increase the stock of immigrants and examine the relative impact of admitting pools of immigrants with different characteristics. Critically, we study the

<sup>18</sup>We note that empirical estimates vary depending on the specification or time horizon given the small number of observations in the data used to estimate these effects. However, in these scenarios, the estimated effects of the inflow of Mariel immigrants on labor market outcomes are smaller for natives and relatively larger for immigrants, a result that is consistent with our model-based estimates.

Table 8: Immigration policy: Productivity gains from admitting new immigrants

Category	Immigrant type/subtype	Baseline model (%)	No immigrant wedge model (%)
All		0.04	2.89
Age	25-34	0.04	2.71
	35-44	0.02	3.15
	45-54	0.02	2.84
Gender	Male	0.04	2.85
	Female	0.02	2.91
Education	Less than high school	-0.09	3.18
	High school	-0.01	3.11
	Less than college	0.08	2.64
	College	0.09	2.66
Country of origin	High-income country	0.11	2.76
	Middle-income country	-0.02	2.65
	Low-income country	0.07	3.24
English proficiency	No English	-0.12	2.33
	Some English	-0.02	3.10
	Fluent English	0.08	2.90

*Notes:* This table presents percent changes in output per hour (TFP) when we increase the total mass of a given recent immigrant (type, subtype) pair such that the total mass of all immigrants in the economy increases by 10 percent. The first column shows percent changes in TFP in an economy with immigrant wedges (baseline model) when we implement such an increase in immigrant mass. The second column repeats the same exercise in an economy without immigrant wedges (no immigrant wedge model).

extent to which immigrant barriers affect the predicted impact of such immigration policies.

We consider an inflow of new immigrants that raises the total immigrant mass by 10%—i.e., from 19% to 20.9% of the U.S. population in the 25-54 age group. We compute the implications for real output per hour (TFP) to isolate the impact of increased immigration on productivity from its mechanical impact on output. We contrast alternative approaches to immigration by varying the composition of the pool of newcomers, as detailed below. The first column of Table 8 shows the percent changes in productivity in an economy with immigrant wedges (baseline model) when we implement the alternative policies one at a time. The second column repeats this exercise in an economy sans immigrant wedges (no immigrant wedge model).

We begin by examining the effects of these policies in the baseline model. The first row of the table reports the effects of increasing immigration, as described above, when considering a pool of new immigrants whose distribution across types and subtypes is identical to the current distribution of recent immigrants in the U.S. We find that this policy change increases productivity by 0.04%. That is, we find that new immigrants not only mechanically increase total output, but also increase the aggregate productivity of the economy.

Row 2 up to the last show the effects of increasing immigration when the pool of new immi-

grants is restricted to a particular immigrant type or subtype.<sup>19</sup> We also find that the impact of increasing immigration differs substantially depending on the composition of the pool of new immigrants. Productivity gains are higher when the immigration policy favors those who are college educated over those who are not, those who are fluent in English over those who are not, and those who are from high-income countries over those who are from low-income countries.

The second column of Table 8 shows that the impact of increased immigration depends critically on the extent to which immigrants are subject to barriers. Overall, we find that *simultaneously* removing immigrant barriers and admitting new immigrants significantly amplifies the productivity gains from increased immigration. Importantly, we also find that the ranking of productivity gains from admitting a particular type of immigrant changes if immigrant wedges are removed. For instance, we find that in the absence of immigrant-specific distortions, the productivity gains are particularly amplified when the U.S. admits disadvantaged immigrant groups—less educated, with some English fluency, and from low-income countries. While in the presence of immigrant barriers, the gains from admitting college-educated immigrants are larger than the gains from those who are not. Importantly, the opposite becomes true when new immigrants face no barriers. The same is also true when comparing outcomes between admitting immigrants with some English and immigrants who are fluent, or immigrants from low-income countries and those from high-income countries: Gains become larger for admitting the former (disadvantaged) groups only if they also face no barriers.

## 6 Immigrant Wedges Across Countries

The previous sections demonstrated that the immigrant barriers in the U.S. have sizable aggregate, distributional, and policy implications. The quantitative significance of these barriers motivates a deeper understanding of the underlying drivers of immigrant wedges and the gains associated with their removal. In this section, we exploit cross-country variation in immigrant labor market outcomes in the data and estimated immigrant wedges in the model to achieve these objectives. First, using our model and cross-country microdata, we compute the magnitudes of immigrant wedges across countries and their macroeconomic implications. Second, we use cross-country differences in immigrant labor market outcomes to provide further insights on underlying labor market features that determine the gains from removing immigrant wedges.

**Data.** We use cross-country survey data from the Luxembourg Income Study (LIS) database, which collects information from surveys originally conducted by national institutions in each respective country. The LIS publishes data in waves that are typically three to five years apart. For each country in the LIS database, we use all available data between 2010 and 2019.<sup>20</sup>

---

<sup>19</sup>We assume that the distribution of new immigrants across the remaining types and subtypes is the same as in the overall U.S. distribution of recent immigrants.

<sup>20</sup>In our sample, 8 of 19 countries have data for all years between 2010 and 2019, while all other countries except Russia have data more than one year. For each country, we pool all available years together to increase

The LIS database contains person-level data on labor income, labor market outcomes (including employment status, occupation, weeks worked in a year, and usual weekly hours worked), demographics (including education, age, and gender), as well as immigration status.<sup>21</sup> To maximize the comparability of empirical targets across countries and the set of countries in our sample, and at the same time keep the empirical implementation as similar as possible to our analysis using the ACS in Section 3.1, we make the following choices in the LIS data.

First, individuals are partitioned into types and subtypes as in Section 3.1, but with a few exceptions. Given data limitations, we abstract from differences across immigrants by time since immigration, fluency in the language of the host country, and the income level of the country of origin. Further, we maximize comparability across countries by considering two education categories, i.e., non-college vs. college. As in the ACS, we restrict our sample to non-business owners between the ages of 25 and 54 who are not on active military duty.

Second, the LIS database provides information on the current occupation of employed individuals, where occupations for each country are based on either the International Standard Classification of Occupations (ISCO) codes or the country’s own occupation classification. We map each country’s occupation classification into the SOC by using crosswalks between the ISCO and SOC for countries with ISCO codes, and crosswalks between country-specific occupation codes and the ISCO and then between the ISCO and SOC for the remaining countries. Because occupation categories are less-detailed in some countries relative to others, to maximize comparability across countries, we classify each individual’s reported occupation into one of four task-based occupation categories as in Autor and Dorn (2013).<sup>22</sup> This process allows us to harmonize the classification of occupations into broad occupation groups across countries.

Our final sample consists of 19 countries with harmonized target moments on the distribution, annual earnings, and hourly wages of individuals across demographics and occupations. Appendix B.2 provides more details about the data and measurement.

**Labor market outcomes of immigrants across countries.** We start by documenting salient differences in labor market outcomes between immigrants and natives across countries. We focus on the distribution of immigrants and natives across occupations as well as their average annual earnings and hourly wages in each occupation since these are the moments used to estimate the model. Specifically, for each country, we first calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives), as well as their associated average annual earnings and hourly wages in each occupation. Then, for each occupation, we

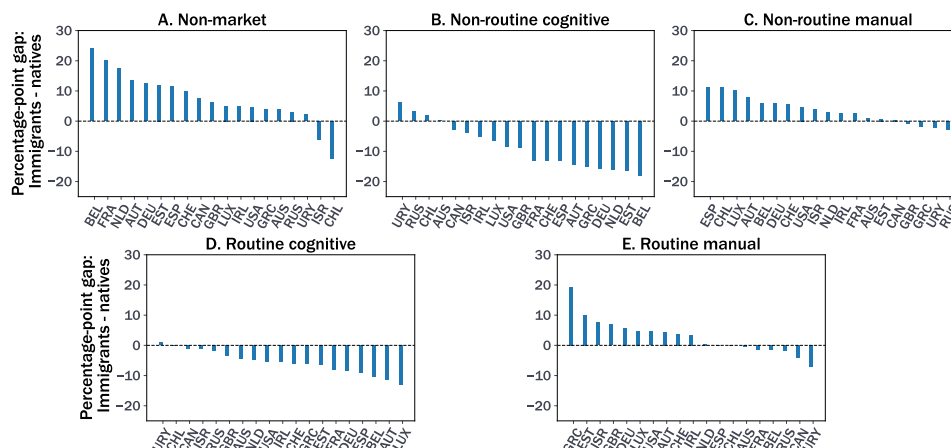
---

the sample size and treat them as one cross section.

<sup>21</sup>Similar to the ACS, we define an immigrant to be a foreign-born individual. Moreover, income is provided in each country’s local currency. We use the purchasing power parity (PPP) and consumer price index (CPI) data provided by LIS to convert income amounts over time and across countries into 2019 U.S. dollars.

<sup>22</sup>In addition, some individuals are classified to be in the non-market occupation, using the same definition of the non-market occupation as in Section 3.1.

Figure 3: Cross-country differences in allocations between immigrants and natives



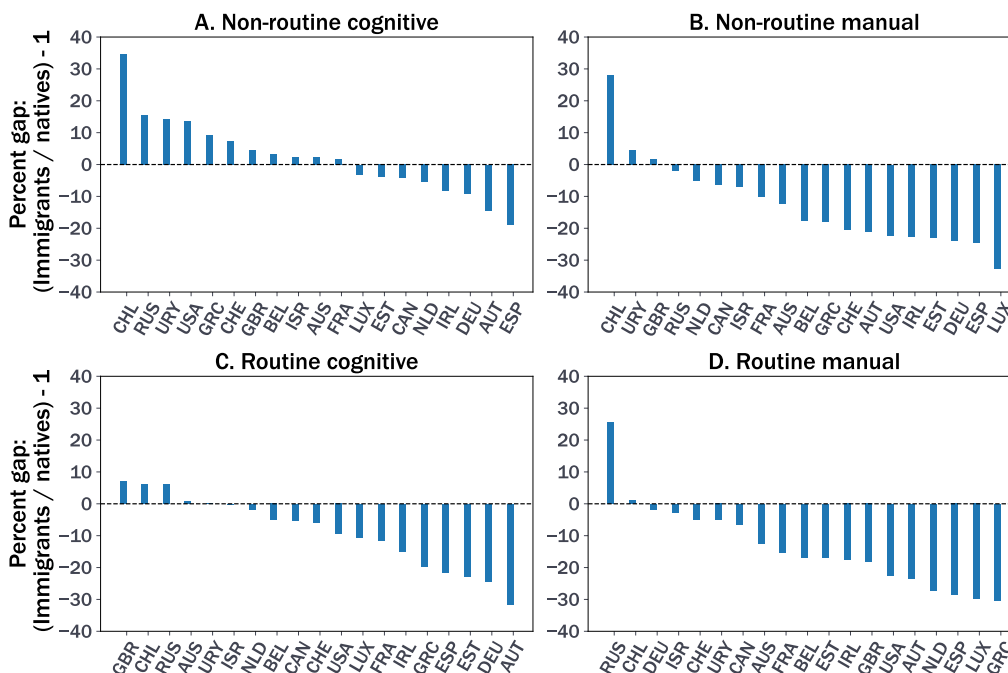
*Notes:* This figure presents differences in labor market allocations between immigrants and natives across countries using data from the LIS. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives). The figure shows the percentage-point gap (calculated as immigrants – natives) between fractions of immigrants and natives in each occupation across countries.

calculate (i) the percentage-point gap (expressed as immigrants – natives) between the fraction of immigrants and natives that work in the occupation and (ii) the percent gap (expressed as immigrants/natives – 1) between the annual earnings of immigrants and natives. Figures 3 and 4 plot these two moments across countries, respectively. We also calculate the same percent gap between hourly wages of immigrants and natives and provide this result in Figure A1.

We highlight salient differences across countries in the allocation of immigrants and natives across occupations. First, while the fraction of immigrants in the non-market occupation is higher than that of natives in almost all countries, this gap varies significantly across countries. For example, while this gap is around 5 percentage points (pp) in the U.S. (USA) and the U.K. (GBR), it is 24 pp in Belgium (BEL), 20 pp in France (FRA), and 13 pp in Germany (DEU). Second, immigrants are underrepresented in non-routine cognitive occupations (the occupation with the highest average earnings in all countries) and overrepresented in non-routine manual occupations (the occupation with the lowest average earnings in all countries) in almost all countries. Notably, there are sizable differences in the gaps between the fractions of immigrants and natives in these occupations across countries. For instance, while the fraction of immigrants in non-routine cognitive occupations is 8 pp (16 pp) lower than that of natives in the U.S. (Germany), immigrants and natives are equally represented in this occupation in Australia (AUS). On the other hand, while the fractions of immigrants and natives in non-routine manual occupations are similar in France, Canada (CAN), and the U.K., immigrants are overrepresented in these occupations especially in Spain (ESP) and Chile (CHL).

Figure 4 presents the annual earnings gaps between immigrants and natives across countries and occupations. Interestingly, we find that, in 11 of 19 countries in our sample, the average earnings of immigrants are larger than those of natives in non-routine cognitive occupations,

Figure 4: Cross-country differences in annual earnings between immigrants and natives



Notes: The figure shows the percent gap (calculated as immigrants/natives - 1) between annual earnings of immigrants and natives in each occupation across countries using data from the LIS.

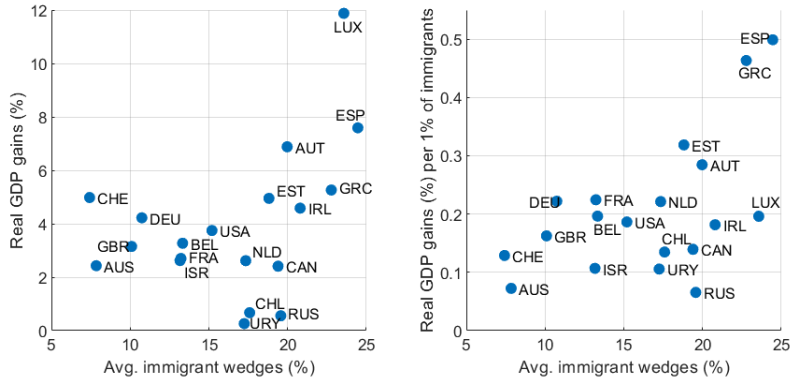
exhibiting significant dispersion across countries. For example, in these occupations, the average earnings of immigrants are 35% and 14% larger than those of natives in Chile and the U.S., respectively, but 19% and 14% lower than those of natives in Spain and Austria (AUT), respectively. On the other hand, the average earnings of immigrants are significantly lower than those of natives in non-routine manual occupations across most countries, but the magnitudes of these earnings gaps exhibit significant heterogeneity: Relative to natives, immigrants in these occupations earn 24% less in Germany, 22% less in the U.S., and 10% less in France.<sup>23</sup>

We note that differences in labor market outcomes between immigrants and natives across countries can be driven by differences in their demographics. Figures A2, A3, and A4 document how allocations and annual earnings gaps between immigrants and natives differ across countries along various gender, education, and age groups, respectively. These results emphasize the importance of accounting for demographic differences between immigrants and natives across countries when estimating the productivity and wedge parameters of the model.

**Immigrant wedges across countries: Estimates and aggregate effects.** The evidence above shows that differences in the labor market outcomes between immigrants and natives vary substantially across countries. We now investigate the extent to which these differences reflect differences in immigrant wedges across countries or are accounted for by cross-country differences

<sup>23</sup>Figure A1 shows that these conclusions largely hold when we analyze the hourly wage gaps as well.

Figure 5: GDP gains from removing immigrant wedges across countries



*Notes:* This figure shows how GDP gains from removing immigrant wedges vary across countries. The left panel presents a cross-country comparison of the sizes of average immigrant compensation wedges and the percent increases in real GDP associated with removing immigrant wedges. The right panel plots real GDP gains adjusted for the immigrant share in the population against the average immigrant compensation wedges.

in immigrants’ productivities or preferences. To do so, we separately estimate the model for each country in our sample, following the approach described in Section 3. Then, for each country, we compute the effects of removing immigrant wedges as in Section 4.

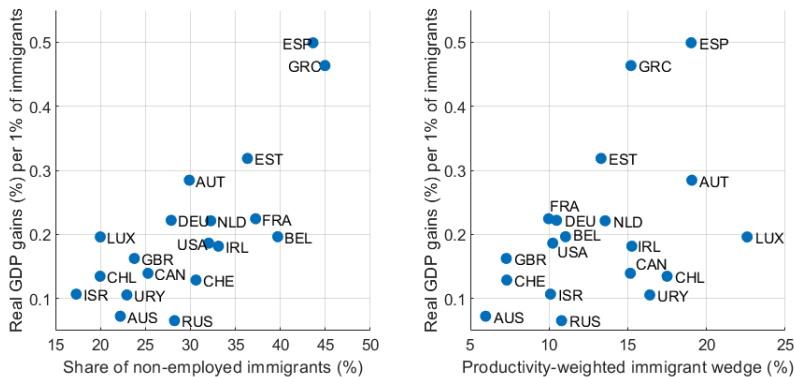
The left panel of Figure 5 presents the relation between the average of immigrant compensation wedges across countries (x-axis) and real GDP gains from removing immigrant wedges (y-axis).<sup>24</sup> We find that there is a large degree of dispersion in immigrant barriers (from 7.42% in Switzerland (CHE) to 24.46% in Spain), which is mirrored by substantial dispersion in the output gains from removing these wedges across countries (from 0.26% in Uruguay (URY) to 11.87% in Luxembourg (LUX)).<sup>25</sup> However, we find that the average immigrant compensation wedges is not a sufficient statistic for determining the output gains from removing immigrant barriers: The correlation between them is 0.41. That is, conditional on a given average level of immigrant compensation wedges, substantial dispersion remains. For example, even if the average immigrant compensation wedges is similar in Spain and Greece (GRC), output gains from removing immigrant wedges are much larger in Spain than in Greece (7.59% vs 5.26%).

One potential explanation for the dispersion of real GDP gains conditional on a given level of the average immigrant wedges is the heterogeneity across countries in the share of immigrants in the population. For a given level of wedges, the model mechanically implies that countries with larger immigrant populations feature larger gains from removing wedges simply because there are more individuals whose occupational choices are distorted. We control for this channel in the right panel of Figure 5, where we reproduce the left panel of the figure but instead plot

<sup>24</sup>We focus on immigrant compensation wedges, as they account for most of the output gains.

<sup>25</sup>Recall that real GDP gains from removing wedges in the U.S. was 6.98% when the model is estimated using the ACS. However, when the model is estimated using the LIS with less degrees of heterogeneity in worker and occupation types due to data limitations, real GDP gains in the U.S. are 3.75%. This difference between the estimated GDP gains from removing wedges in the U.S. using the ACS and the LIS reflects that accounting for heterogeneity is relevant for understanding gains from removing wedges, a result that we discuss in Section 8.

Figure 6: Sources of GDP gains from removing immigrant wedges across countries



*Notes:* This figure shows the underlying channels that account for differences in GDP gains per immigrant from removing immigrant wedges across countries. The left panel presents the share of non-employed immigrants among all immigrants against the GDP gains per immigrant. The right panel plots the average immigrant compensation wedges weighted by the occupation and individual specific productivities against the GDP gains per immigrant.

GDP gains per immigrant instead of total GDP gains. This adjustment tightens the relation between average immigrant compensation wedges and GDP gains, increasing the correlation between both variables from 0.41 to 0.55. The gains per immigrant now become much closer in Spain and Greece despite the much larger differences in the implied total gains.

Despite the increased correlation between wedges and the gains from removing them, significant heterogeneity remains conditional on a given level of immigrant wedges. For example, Canada and Greece have comparable levels of average immigrant compensation wedges, but the output gains per immigrant from removing immigrant wedges are much larger in Greece (0.46%) than in Canada (0.14%). Two channels likely play a significant role in accounting for this residual heterogeneity. First, the gains from removing immigrant barriers depend on the share of immigrants that are non-employed prior to removing the barriers—an extensive margin channel. A country with a high fraction of non-employed immigrants is likely to experience a large inflow of individuals into market occupations when wedges are removed and market occupations become more appealing. Second, the distribution of immigrant wedges can have a significant impact on the gains from removing immigrant barriers—an intensive margin channel. To the extent that more-productive occupations or individuals face larger distortions, the reallocation of workers across occupations when wedges are removed is likely to imply larger gains.

We study the role of these channels in Figure 6. The left panel plots real GDP gains per immigrant as a function of the fraction of non-employed immigrants, while the right panel plots the gains against the average of the immigrant compensation wedges weighted by the productivity  $A_j$  of each occupation and the productivity  $z$  of each individual type and subtype. We find that both of these channels are important determinants of the gains from removing immigrant wedges. First, the left panel shows that there is substantial heterogeneity across countries in the share of non-employed immigrants. Moreover, the immigrant non-employment share is also positively correlated with the implied gains. Second, the right panel shows that gains from removing



wedges are typically larger in countries with larger productivity-weighted immigrant wedges.

Two examples illustrate how output gains can be driven by either of these channels. For the extensive margin channel, we compare Canada and Greece, two countries with similar average immigrant compensation wedges as observed in the right panel of Figure 5, but with considerable differences in the implied output gains per immigrant. We observe that the average productivity-weighted immigrant wedges are also nearly identical between them, but Greece has a much larger fraction of non-employed immigrants (45% vs. 25% in Canada). This suggests that the larger inflow of immigrants from the non-market occupation to market occupations is the main driver behind the larger gains in Greece over Canada. For the intensive margin channel, we compare outcomes between the Netherlands and the U.S., which have similarly sized average immigrant compensation wedges and similar fractions of non-employed immigrants. Yet, gains per immigrant from removing wedges are larger in the Netherlands (0.22%) than in the U.S. (0.19%). This is because the productivity-weighted wedges are larger in the Netherlands (14%) than in the U.S. (10%). Thus, removing wedges in the Netherlands leads to larger gains because immigrant wedges are higher for high-productivity occupations and workers than in the U.S.

## 7 Immigrant Wedges: Model vs External Evidence

To provide some insights on what immigrant wedges may capture in reality, we compare estimates of immigrant wedges with external evidence on the degree to which immigrants face barriers.

### **Immigrant wedges across occupations in the U.S.: Model vs external evidence.**

We first compare model-implied immigrant wedges across occupations in the U.S. presented in Section 4 with an obvious barrier that newcomers face: country-specific licensing requirements.

Since 2016, the Current Population Survey (CPS) provides information on whether a respondent’s existing job requires a government-issued professional, state, or industry license. We pool the CPS data between 2016 and 2019 and calculate the fraction of jobs requiring a license for each of the 25 market occupations described in Section 3.1.<sup>26</sup> As expected, we find that the fraction of jobs requiring a license is the highest in healthcare, legal, education, healthcare support, and protective services occupations, while it is the lowest in cleaning and maintenance, admin, and agriculture occupations. We compare this measure of intensity in licensing with immigrant compensation wedges and immigrant labor supply wedges implied by our model in Section 4.

Table 9 reports correlations between model-implied immigrant wedges and the fraction of jobs requiring a license across occupations in the U.S. We find that all correlations are positive, indicating that model-implied immigrant wedges are larger in occupations where license requirements are more prevalent. Importantly, we find that these correlations are higher when we compare licensing requirements with immigrant wedges for recent immigrants, but correla-

---

<sup>26</sup>Using the CPS, we also apply the same sample selection and definition of being employed as in Section 3.1.

Table 9: Immigrant barriers across occupations: Model estimates vs external evidence

Model-implied measures	Fraction of jobs requiring a license
Average immigrant compensation wedge:	
all immigrants	0.09
recent immigrants	0.23
established immigrants	-0.01
Average immigrant labor supply wedge:	
all immigrants	0.16
recent immigrants	0.31
established immigrants	0.03

*Notes:* This table reports correlations between the fraction of jobs that require a license with model-implied measures of immigrant wedges across occupations in the U.S. We use the CPS data between 2016 and 2019 to calculate the fraction of jobs requiring a license for each of the 25 market occupations, same as in our analysis in Section 3.1.

tions almost disappear when wedges for established immigrants are used. This result suggests that recent immigrants face large barriers due to occupational licensing requirements, but these barriers eventually lessen over time as immigrants obtain credentials.

**Immigrant wedges across countries: Model vs. external evidence.** Next, we move to comparing immigrant wedges across countries presented in Section 6 with external evidence on the degree to which immigrants face barriers.

We focus on four measures of immigrant wedges implied by our model: average immigrant compensation wedges, average immigrant labor supply wedges, growth of aggregate productivity (TFP) upon removal of immigrant wedges, and growth of real GDP per 1% of immigrants upon removal of immigrant wedges. The first two capture the extent to which immigrants' choices might be distorted, while the latter two capture the aggregate effects of such distortions.

We contrast these model-implied measures of immigrant wedges with two external cross-country indexes on the degree to which immigrants face barriers to integration upon arrival. The first index is the Migrant Acceptance Index (MAI) collected by Fleming et al. (2018), which is designed to compare the attitudes toward immigrants across countries. This is done by exploiting the rich survey data from the Gallup World Poll, which directly asks individuals across countries about their attitudes toward immigrants.<sup>27</sup> The second index is the Migrant Integration Policy Index (MIPEX) collected by Solano and Huddleston (2020), which is designed to compare immigrant policies across countries.<sup>28</sup> Higher values of these indexes indicate attitudes or policies

<sup>27</sup>The questions asked cover whether people think migrants living in their country, becoming their neighbors, and marrying into their families are good things or bad things.

<sup>28</sup>These include (but not limited to) measures on how easy for immigrants to gain permanent residence and citizenship in the host country, whether immigrants have equal rights and opportunities to access jobs and improve their skills, how easy immigrants can reunite with their family, and whether health and education systems are responsive to the needs of immigrants and their children.

Table 10: Immigrant barriers across countries: Model estimates vs external evidence

Model-implied measures	MAI	MIPEX
Average immigrant compensation wedge	-0.15	-0.33
Average immigrant labor supply wedge	-0.14	-0.23
TFP gains from removing immigrant wedges	-0.32	-0.22
Real GDP gains per 1% of immigrants from removing immigrant wedges	-0.09	-0.14

*Notes:* This table reports correlations between external measures on the degree to which immigrants face barriers with model-implied measures of immigrant wedges and TFP and output gains from removing these wedges. We focus on two external measures: MAI denotes the Migrant Acceptance Index reported in Fleming et al. (2018), while MIPEX denotes the Migrant Integration Policy Index from Solano and Huddleston (2020). These two measures are designed to compare attitudes and policies toward immigrants across countries, respectively. Higher values of these indexes indicate attitudes or policies that are more friendly toward immigrants.

that are more friendly toward immigrants.

To contrast the model-implied measures of immigrant wedges with these external estimates, we compute the correlation between them for the countries for which these indexes overlap with the set of countries that we study.<sup>29</sup> Table 10 reports correlations between these external measures with model-implied wedges and the impact of these wedges in the aggregate.

We find that the model-implied estimates of immigrant barriers are consistent with these external indices. In particular, we find that all of the correlations are negative, reflecting that countries with better attitudes or policies toward immigrants (i.e., higher values of the external indexes) are estimated to feature lower immigrant wedges and gains from their removal.

## 8 Discussion of Results

We conclude our analysis by examining the role played by model specifications and parameter values in accounting for our findings. To do so, we focus on the analysis for the U.S. from Section 4. We report our findings in Table 11.

**Modeling heterogeneity and endogenous labor supply.** We examine the importance of accounting for rich heterogeneity in occupations and worker types. To do so, we first estimate the model classifying market occupations into just four broad (task-based) occupation categories instead of 25 as in the baseline U.S. economy. We then compare outcomes between this economy and the same economy without immigrant wedges. We find that real GDP gains from removing immigrant wedges are much lower (2.50%) in this case relative to the baseline (6.98%). A key channel that accounts for these findings is that fewer occupations limit the reallocation across occupations once wedges are removed. As such, TFP gains are negligible in this coarser approach.

Next, we implement a similar exercise but instead reduce the number of worker groups by distinguishing immigrants *only* by the income level of their country of origin, and only consider subtypes of natives and immigrants by education. Thus, we are left with just 16 worker groups

<sup>29</sup>While all the countries in our LIS sample are also available in MAI, Uruguay is not available in MIPEX.

instead of the 456 groups in the baseline. Table 11 shows that gains from removing wedges in this case are also significantly reduced. This result is intuitive given that there is much less scope for misallocation due to wedges when the model does not sufficiently differentiate worker types.

Finally, we examine the role of elastic labor supply by considering a version of the model that abstracts from this channel. Table 11 shows that, in a model with inelastic labor supply, real GDP gains from removing immigrant wedges drop to 2.75%. Relative to the baseline model, the smaller gains are driven by two margins. First, there is one less margin of adjustment when wedges are removed—that is, there are no gains from changes in hours worked. Second, TFP gains are also lower because when workers shift to occupations for which they are more productive, they cannot adjust their hours worked, limiting TFP gains from reallocation.

Overall, we conclude that accounting for rich heterogeneity in occupations and worker groups as well as modeling the endogenous labor supply margin are important for the aggregate gains from removing immigrant wedges.

**Heterogeneous productivity distributions between natives and immigrants.** In our baseline estimation, we assume that idiosyncratic productivities of natives and immigrants across occupations are drawn from a common Frechet distribution, motivated by empirical findings in [Martellini, Schoellman, and Sockin \(2023\)](#). We now provide our main results when we instead assume that idiosyncratic productivities are drawn from different distributions. Specifically, we assume that the shape parameter of the Frechet distribution is different for immigrants such that the mean of productivity draws is 10% higher for immigrants than for natives. We do so by changing the shape parameter of the distribution for immigrants, keeping it unchanged for natives. A higher mean of the idiosyncratic productivity draws for immigrants implies that immigrants’ productivity distribution across occupation is more dispersed than natives. Thus, immigrant wedges affect the allocation of immigrants across occupations relatively less, leading to lower misallocation due to immigrant wedges and lower aggregate gains from removing them in this case relative to the baseline.

**Alternative parameter values.** Finally, we examine our main findings under *(i)* alternative production technologies that differ in how labor bundles are aggregated across worker types and subtypes (e.g., different nesting as well as different elasticities), and *(ii)* alternative values for other predetermined parameters. Table A6 in Appendix E summarizes our results. Overall, our main results are similar to our baseline results with two intuitive exceptions: A lower substitutability of labor bundles between natives and all immigrants or a lower substitutability of labor bundles across different immigrant types leads to larger gains from removing wedges.

Table 11: Gains from removing immigrant wedges under alternative specifications

	Percent change				Change in immigrant share (pp)
	Real GDP	TFP	Employment	Hours	
Baseline	6.98	2.48	1.91	2.43	1.62
Fewer occupations	2.50	0.03	1.40	1.05	1.18
Fewer worker groups	1.68	-0.58	1.74	0.52	1.45
Inelastic labor supply	2.75	0.77	1.94	0.00	1.66
Higher productivity draws for immigrants	4.48	1.38	1.50	1.54	1.27

*Notes:* This table presents the percent change in aggregate real GDP, TFP, employment, and hours when immigrant wedges are set equal to their counterpart natives of the same subtype under alternative model specifications. Baseline refers to our baseline model; fewer occupations refers to an exercise where market occupations are grouped into four broad (task-based) occupation categories; fewer worker groups refers to an exercise where we distinguish immigrants only by the income level of their country of origin, and only consider subtypes of natives and immigrants by education; and higher productivity draws for immigrants refers to a model where the shape parameter of the Fréchet distribution is different for immigrants such that the mean of productivity draws is 10% higher for immigrants than for natives.

## 9 Conclusion

In this paper, we quantify the labor market barriers faced by immigrants in the U.S. and across countries. We find that immigrant barriers are pervasive across countries, sizable, and heterogeneous across worker types and occupations.

We show that the gains from removing immigrant barriers in the U.S. are around 7% of GDP. These gains arise from both increased employment and average hours worked as well as from the improved allocation of immigrants across occupations. The gains are also distributed unevenly, with recent immigrants, those with less education or English fluency, and those from low-income countries poised to benefit the most. Across countries, we find large variations in immigrant wedges and associated gains from removing them, with the U.S. exhibiting a level of immigrant wedges and implied gains from removing them close to the averages across the countries in our sample. We show that the gains from removing these wedges are affected by the prevalence of immigrant non-employment as well as the concentration of wedges for high-productivity occupations and workers. Importantly, we also show that estimated immigrant wedges in our model are correlated with occupation-specific licensing requirements in the U.S. and indexes on attitudes and policies toward immigrants across countries. Finally, we demonstrate that immigrant wedges affect the impact of alternative immigration policies. Thus, our results suggest that policymakers should jointly address immigrant entry as well as labor market integration *after* entry.

Our analysis abstracts from how wedges affect individuals' decisions to immigrate to other countries. The magnitudes and distributions of immigrant wedges across individuals and occupations may affect the composition of immigrants that decide to immigrate to another country. This may in turn have implications on gains from removing wedges and affect the impact of alternative immigration policies. We leave these considerations for future research.

# References

- ALBERT, C. (2021): “The labor market impact of immigration: Job creation versus job competition,” *American Economic Journal: Macroeconomics*, 13, 35–78.
- ALBERT, C., A. GLITZ, AND J. LLULL (2021): “Labor market competition and the assimilation of immigrants,” Tech. rep., Universitat Autònoma de Barcelona.
- ALBERT, C. AND J. MONRAS (2021): “Immigration and spatial equilibrium: The role of expenditures in the country of origin,” Tech. rep.
- AUTOR, D. H. AND D. DORN (2013): “The growth of low-skill service jobs and the polarization of the U.S. labor market,” *American Economic Review*, 103, 1553–97.
- BARTELSMAN, E., J. HALTIWANGER, AND S. SCARPETTA (2013): “Cross-country differences in productivity: The role of allocation and selection,” *American Economic Review*, 103, 305–34.
- BENTO, P. AND D. RESTUCCIA (2017): “Misallocation, establishment size, and productivity,” *American Economic Journal: Macroeconomics*, 9, 267–303.
- BORJAS, G. J. (2017): “The wage impact of the Marielitos: A reappraisal,” *ILR Review*, 70, 1077–1110.
- BUERA, F. J., J. P. KABOSKI, AND Y. SHIN (2011): “Finance and development: A tale of two sectors,” *American Economic Review*, 101, 1964–2002.
- BURSTEIN, A., G. HANSON, L. TIAN, AND J. VOGEL (2020): “Tradability and the labor-market impact of immigration: Theory and evidence from the United States,” *Econometrica*, 88, 1071–1112.
- CARD, D. (1990): “The impact of the Mariel boatlift on the Miami labor market,” *ILR Review*, 43, 245–257.
- CORTES, G. M., N. JAIMOVICH, C. J. NEKARDA, AND H. E. SIU (2020): “The dynamics of disappearing routine jobs: A flows approach,” *Labour Economics*, 65, 101823.
- DOSTIE, B., J. LI, D. CARD, AND D. PARENT (2020): “Employer policies and the immigrant-native earnings gap,” Tech. rep., National Bureau of Economic Research.
- DUSTMANN, C., U. SCHÖNBERG, AND J. STUHLER (2016): “The impact of immigration: Why do studies reach such different results?” *Journal of Economic Perspectives*, 30, 31–56.
- FLEMING, J. H., N. ESİPOVA, A. PUGLIESE, J. RAY, AND R. SRINIVASAN (2018): “Data survey: Migrant Acceptance Index: A global examination of the relationship between interpersonal contact and attitudes toward migrants,” *Border Crossing*, 8, 103–132.
- GOPINATH, G., Ş. KALEMLİ-ÖZCAN, L. KARABARBOUNIS, AND C. VILLEGAS-SANCHEZ (2017): “Capital allocation and productivity in South Europe,” *Quarterly Journal of Economics*, 132, 1915–1967.
- HANSON, G. H. AND C. LIU (2021): “Immigration and occupational comparative advantage,” Tech. rep., National Bureau of Economic Research.
- HENDRICKS, L. (2002): “How important is human capital for development? Evidence from immigrant earnings,” *American Economic Review*, 92, 198–219.
- HENDRICKS, L. AND T. SCHOELLMAN (2018): “Human capital and development accounting: New evidence from wage gains at migration,” *Quarterly Journal of Economics*, 133, 665–700.
- HOPENHAYN, H. A. (2014): “Firms, misallocation, and aggregate productivity: A review,” *Annual Review of Economics*, 6, 735–770.
- HSIEH, C.-T., E. HURST, C. I. JONES, AND P. J. KLENOW (2019): “The allocation of talent and U.S. economic growth,” *Econometrica*, 87, 1439–1474.
- HSIEH, C.-T. AND P. J. KLENOW (2009): “Misallocation and manufacturing TFP in China and India,” *Quarterly Journal of Economics*, 124, 1403–1448.
- LAGAKOS, D., B. MOLL, T. PORZIO, N. QIAN, AND T. SCHOELLMAN (2018a): “Life-cycle human capital accumulation across countries: lessons from US Immigrants,” *Journal of Human Capital*, 12, 305–342.

- (2018b): “Life cycle wage growth across countries,” *Journal of Political Economy*, 126, 797–849.
- LLULL, J. (2018): “Immigration, wages, and education: A labour market equilibrium structural model,” *Review of Economic Studies*, 85, 1852–1896.
- LUXEMBOURG INCOME STUDY (LIS) DATABASE (2010-2019): <https://www.census.gov/programs-surveys/sipp.html>.
- MARTELLINI, P., T. SCHOELLMAN, AND J. SOCKIN (2023): “The global distribution of college graduate quality,” *Journal of Political Economy*, forthcoming.
- MONRAS, J. (2020): “Immigration and wage dynamics: Evidence from the Mexican peso crisis,” *Journal of Political Economy*, 128, 3017–3089.
- OTTAVIANO, G. I. AND G. PERI (2012): “Rethinking the effect of immigration on wages,” *Journal of the European Economic Association*, 10, 152–197.
- PERI, G. AND V. YASENOV (2017): “The labor market effects of a refugee wave: Applying the synthetic control method to the Mariel boatlift,” Tech. rep., National Bureau of Economic Research.
- PIYAPROMDEE, S. (2021): “The impact of immigration on wages, internal migration, and welfare,” *Review of Economic Studies*, 88, 406–453.
- RESTUCCIA, D. AND R. ROGERSON (2008): “Policy distortions and aggregate productivity with heterogeneous establishments,” *Review of Economic Dynamics*, 11, 707–720.
- ROY, A. D. (1951): “Some thoughts on the distribution of earnings,” *Oxford Economic Papers*, 3, 135–146.
- SCHOELLMAN, T. (2012): “Education quality and development accounting,” *The Review of Economic Studies*, 79, 388–417.
- (2016): “Early childhood human capital and development,” *American Economic Journal: Macroeconomics*, 8, 145–74.
- SOLANO, G. AND T. HUDDLESTON (2020): *Migrant integration policy index 2020*, ESP.
- U.S. CENSUS BUREAU (2019): American Community Survey public use microdata samples. <https://usa.ipums.org/usa/>.

# Online Appendix

## A Model

In this section, we provide a formal definition of the equilibrium of the model.

Let each individual's idiosyncratic productivity vector be denoted by  $\alpha$ , and let  $\varphi(\alpha)$  denote the probability density function of individuals with vector  $\alpha$ . Let the occupational choice of a type  $i$ , subtype  $g$ , and idiosyncratic productivity vector  $\alpha$  be denoted by  $\mathcal{O}_{ig}(\alpha) \in \{0, \dots, J\}$ .

A *competitive equilibrium* consists of prices  $(p, \{p_j\}_{j=0}^J, \{w_{ig}^j\}_{i,g,j>0}, \{w_k^j\}_{k \in \{\text{nat,imm}\}, j>0}, w^0)$  and allocations  $(y, \{y_j\}_{j=0}^J, \{n_{ig}^j\}_{i,g,j>0}, \{n_k^j\}_{k \in \{\text{nat,imm}\}, j>0}, n^0, \{\mathcal{O}_{ig}(\alpha), \ell_{ig}(\alpha)\}_{i,g})$  such that:

1. Given price  $p$  and wages  $\{w_{ig}^j\}_{j=1}^J$  and  $w^0$ ,  $\mathcal{O}_{ig}(\alpha)$  and  $\ell_{ig}(\alpha)$  solve the problem of each individual of type  $i$ , subtype  $g$ , and productivity vector  $\alpha$ .
2. Given price  $p_j$  and wages  $\{w_k^j\}_k$ ,  $y_j$  and  $\{n_k^j\}_k$  solve the problem of the representative firm in the outer nest of each market occupation  $j = 1, \dots, J$ .
3. For each group  $k \in \{\text{nat,imm}\}$ , given wages  $w_k^j$  and  $\{w_{ig}^j\}_{i \in \mathcal{I}_{k,g}}$ ,  $n_k^j$  and  $\{n_{ig}^j\}_{i \in \mathcal{I}_{k,g}}$  solve the problem of the representative firm in the inner nest of each market occupation  $j = 1, \dots, J$ .
4. Given price  $p_0$  and wage  $w^0$ ,  $y_0$  and  $n^0$  solve the problem of the representative firm in the non-market occupation.
5. Given prices  $p$  and  $\{p_j\}_{j=0}^J$ ,  $y$  and  $\{y_j\}_{j=0}^J$  solve the problem of the final good producer.
6. Aggregate revenue collected through compensation wedges is equal to aggregate reimbursements distributed to individuals:

$$\begin{aligned} & \sum_{i=1}^I \sum_{g=1}^G N_{ig} \sum_{j=0}^J \int_{\alpha} (\tau_g^j + \kappa_{ig}^j) w_{ig}^j z_{ig}^j \varepsilon_j(\alpha) \ell_{ig}(\alpha) \mathbf{I}_{\{j=\mathcal{O}_{ig}(\alpha)\}} \varphi(\alpha) d\alpha \\ &= \sum_{i=1}^I \sum_{g=1}^G N_{ig} \sum_{j=0}^J \int_{\alpha} s(1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig}^j \varepsilon_j(\alpha) \ell_{ig}(\alpha) \mathbf{I}_{\{j=\mathcal{O}_{ig}(\alpha)\}} \varphi(\alpha) d\alpha. \end{aligned}$$

7. Labor market clearing for individuals  $(i, g)$  in market occupation  $j = 1, \dots, J$  is:

$$n_{ig}^j = N_{ig} \times \int_{\alpha} z_{ig}^j \varepsilon_j(\alpha) \ell_{ig}(\alpha) \mathbf{I}_{\{j=\mathcal{O}_{ig}(\alpha)\}} \varphi(\alpha) d\alpha.$$

8. Labor market clearing in the non-market occupation is:

$$n^0 = \sum_{i=1}^I \sum_{g=1}^G \left( N_{ig} \times \int_{\alpha} z_{ig}^0 \varepsilon_0(\alpha) \ell_{ig}(\alpha) \mathbf{I}_{\{0=\mathcal{O}_{ig}(\alpha)\}} \varphi(\alpha) d\alpha \right).$$



9. Market clearing of the final good is:  $\sum_{i=1}^I \sum_{g=1}^G \int_{\alpha} c_{ig}(\alpha) \varphi(\alpha) d\alpha = y$ .

For expositional simplicity, we do not use different notation to denote the demand and supply of occupation-specific goods. Thus, we abstract from the market clearing conditions for such goods, assuming that the same values that solve the problem of occupational goods producers also solve the problem of the final good producer.

## B Data

This section provides details about our main data sets, the ACS and the LIS, respectively.

### B.1 ACS

We use ACS 2010-2019 data to estimate the model for the U.S. In this section, we provide more details about the data, construction of variables, and measurement. In this data, we focus on a sample of non-business owners between the ages of 25 and 54 who are not in military.

The ACS provides information on individuals' citizenship and country of birth. The citizenship variable allows us to identify people who are not U.S. citizens or naturalized citizens, while the country of birth variable allows us to identify people born outside of the U.S. Using these variables, we define immigrants as foreign-born individuals who are either naturalized citizens or not citizens. This implies that natives' foreign-born children are classified as natives.

In our analysis, we consider an economy where immigrants are divided along various dimensions such as time since immigration, English fluency, and the income level of the country of origin. First, the ACS asks the year a foreign-born individual immigrated to the U.S. We use this information to classify immigrants into two groups based on the number of years since immigration: recent immigrants, whose years since immigration is less than or equal to 10 years, and established immigrants, whose years since immigration is higher than 10 years. Second, respondents also provide information on how well they speak English. We group immigrants into three groups based on their English fluency: immigrants who cannot speak English, immigrants who speak English but not well, and immigrants who speak English well (including those who speak only English, those who speak English very well, and those who speak English well). Finally, we divide immigrants into three groups based on the income level of their country of origin. To do so, we use the 2019 GNI per capita data from the World Bank. We define low-income countries as those whose GNI per capita is less than \$3,995 in 2019 U.S. dollars, middle-income countries as those whose GNI per capita is between \$3,995 and \$12,375, and high-income countries as those whose GNI per capita is higher than \$12,375. These cutoffs are the values that the World Bank used in 2019 to divide countries into income groups.<sup>1</sup> In addition

---

<sup>1</sup>The World Bank classifies countries into four groups: low income, lower-middle income, upper-middle income, and high income. In our classifications, we combine the low income and lower-middle income groups into one low-income group to increase the sample size for this group.

Table A1: List of occupations

<b><i>Non-routine cognitive</i></b>	<b><i>Non-routine manual</i></b>
Management, business, science, and arts (10-430)	Healthcare support (3600-3650)
Business operations specialists (500-730)	Protective service (3700-3950)
Financial specialists (800-950)	Food preparation and serving (4000-4150)
Computer and mathematical (1000-1240)	Building and grounds cleaning and maintenance (4200-4250)
Architecture and engineering (1300-1540)	Personal care and service (4300-4650)
Technicians (1550-1560)	<b><i>Routine manual</i></b>
Life, physical, and social science (1600-1980)	Farming, fishing, and forestry (6005-6130)
Community and social services (2000-2060)	Construction (6200-6765)
Legal (2100-2150)	Extraction (6800-6940)
Education, training, and library (2200-2550)	Installation, maintenance, and repair (7000-7630)
Arts, design, entertainment, sports, and media (2600-2920)	Production (7700-8965)
Healthcare practitioners and technicians (3000-3540)	Transportation and material moving (9000-9750)
<b><i>Routine cognitive</i></b>	
Sales and related (4700-4965)	
Office and administrative support (5000-5940)	

*Notes:* This table presents a list of 25 market occupations included in our analysis. Standard Occupational Classification (SOC) codes in the ACS are provided in parenthesis. For expositional purposes, some results in the paper are presented by grouping these 25 market occupations across for broad task-based occupation categories: non-routine cognitive, routine cognitive, non-routine manual, and routine manual. The table above also list occupations grouped under these four categories.

to these dimensions of heterogeneity for the immigrants, we also group immigrants and natives into subtypes based on their education, age, and gender.

We group occupations into 26 categories (25 market occupations and a non-market occupation). Our grouping of market occupations closely follow two-digit 2010 SOC system, where occupations are classified into 23 major groups.<sup>2</sup>

While our estimation and results are based on these 25 market occupations, for expositional purposes, we often present results where we group these 25 market occupations into four task-based occupation categories. Following [Autor and Dorn \(2013\)](#), we group occupations along two dimensions of the characteristics of tasks required for the job: routine vs. non-routine and cognitive vs. manual. We then assign 25 market occupations into one of the four task-based occupation groups as in [Cortes et al. \(2020\)](#). Table A1 presents a list of 25 market occupations, their SOC codes, and their classification into four task-based occupation groups.

## B.2 LIS

**Data.** Here, we provide more details about the LIS data, which is used in our cross-country analysis of immigrant wedges in Section 6. Specifically, we discuss the construction and measurement of variables and provide additional empirical results.

The LIS provides cross-country survey data with individual-level information on labor market

<sup>2</sup>We have 25 market occupations instead of 23 occupations due to the following reasons. First, we do not include military specific occupations, which is one of the occupation categories under SOC system. Second, we separate business and financial operation occupations in the SOC system into two occupation categories (business operations vs finance). Third, we separate technicians from architecture and engineering occupations. Finally, we separate construction and extraction occupations into two occupation categories (construction vs extraction).

outcomes and demographics. LIS data were published every five years from Wave 1 in 1980 to Wave 5 in 2000. Starting with Wave 6 in 2004, new data became available every three years. The latest wave is Wave 11, which collected data between 2018 and 2020. In our analysis, for each country in the LIS database, we use all available data between 2010 and 2019. In our sample, eight out of 19 countries have data for all years between 2010 and 2019, while three other countries have data for all years between 2010 and 2018. On the other hand, we have data for Russia only in 2010 and for Canada only in 2010 and 2011.

The LIS database provides individual-level data on demographics, including immigration status, and labor market outcomes. Similar to the ACS, we define immigrants to be foreign-born individuals. In terms of labor market related variables, the LIS contains individual-level data on employment status (employed or non-employed), self-employment status, usual hours worked in a week, weeks worked in a year, occupation, and total annual labor income. Using this information, we follow the same process to construct our empirical moments on labor market allocations as well as average annual earnings and hourly wages of each (type, subtype) in all occupations (including the non-market occupation) across countries.<sup>3</sup>

Next, we discuss the additional details that are specific to our cross-country analysis using the LIS. The annual labor income of individuals is provided in nominal local currency. We convert labor income amounts to 2019 U.S. dollars using the PPP and CPI data provided by the LIS. We unify occupation codes across countries in the following steps. First, the LIS data provide two-digit ISCO codes for 13 of 19 countries in our sample. For these countries, we use the crosswalk between the ISCO and SOC codes to obtain SOC codes, which then allows us to assign each occupation into one of the four broad occupation groups using the SOC codes of these groups presented in Table A1.<sup>4</sup> Second, for Greece, Israel, and the U.K., the LIS only provides one-digit ISCO codes. Using this information, we assign managers, professionals, and technicians and associate professionals to non-routine cognitive occupations; services and sales workers to non-routine manual occupations; clerical support workers to routine cognitive occupations; and craft and related workers, plant and machine operators and assemblers, and elementary occupations to routine manual occupations.<sup>5</sup> Third, for Australia and Canada, the LIS provides occupation codes based on national occupation classifications. For these two countries, we first use crosswalks between country-specific occupation codes and the ISCO and then between the ISCO and SOC. Once we obtain SOC codes for these countries, we use them to assign occupations into one of the

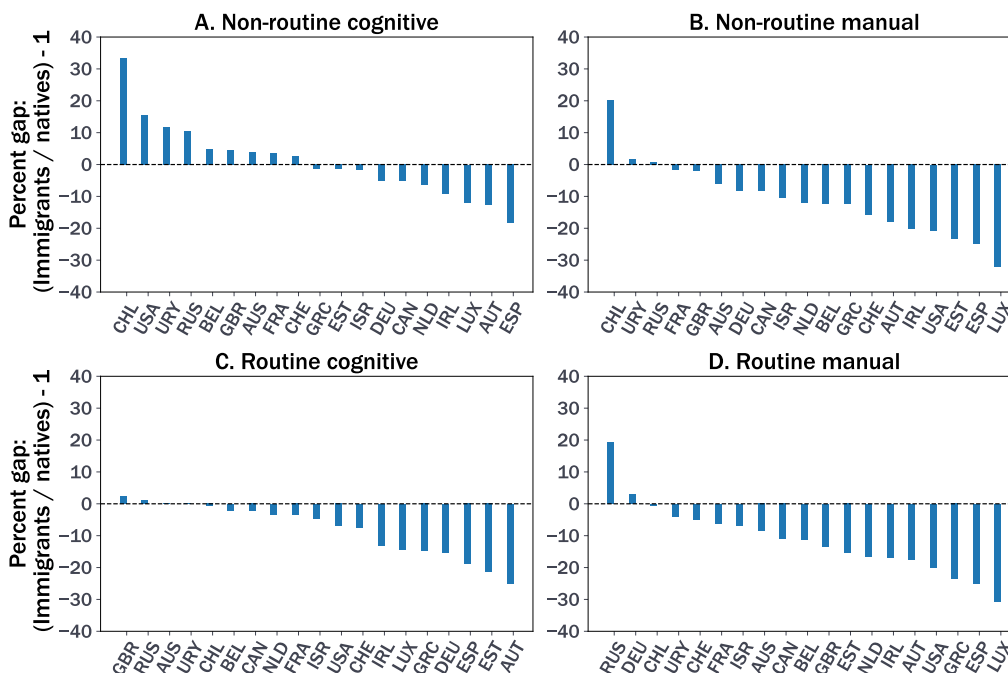
---

<sup>3</sup>For seven countries in our sample, we do not have data on annual weeks worked, which we use together with usual hours worked in a week to calculate total annual hours worked and eventually hourly wages. For each of these countries, we impute annual weeks worked by randomly assigning 52 weeks to 75% of employed and 26 weeks to the remaining 25% of employed population. This imputation is motivated by the fact that, among countries that have information on annual weeks worked, around 75% of employed individuals report working 52 weeks in a year, while the majority of the remaining employed individuals work around 26 weeks.

<sup>4</sup>For France, occupation codes are based on two-digit European Socioeconomic Groups (ESeG) classification, where we use a crosswalk to obtain two-digit ISCO codes from ESeG codes.

<sup>5</sup>These choices are broadly consistent with the one-digit occupation classifications using the SOC codes.

Figure A1: Cross-country differences in hourly wages between immigrants and natives

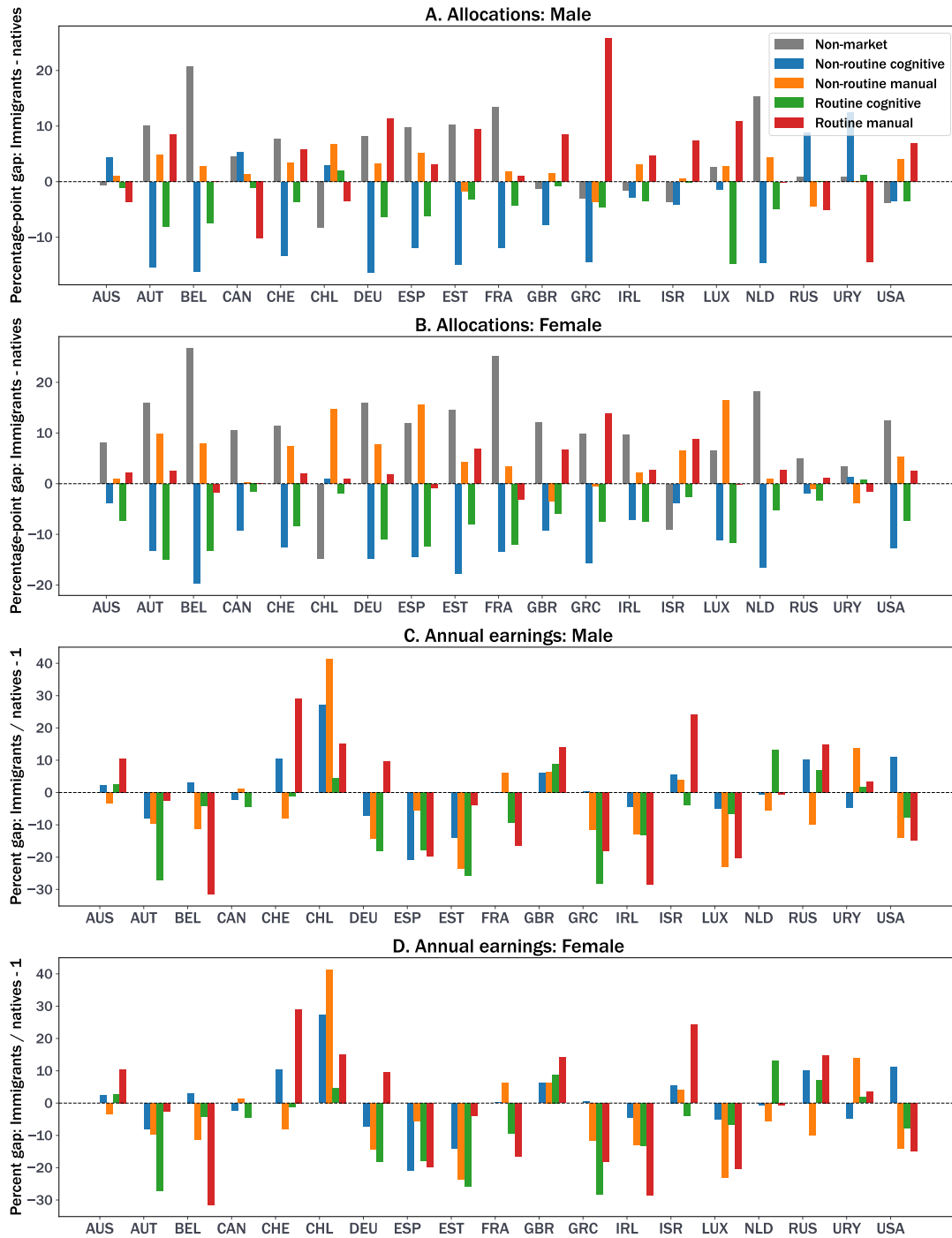


Notes: The figure shows the percent gap (calculated as immigrants/natives - 1) between hourly wages of immigrants and natives in each occupation across countries using data from the LIS.

four broad occupation groups. For the U.S., the LIS already provides occupation codes based on the Census classification. Finally, we also unify occupation codes over time in each country.

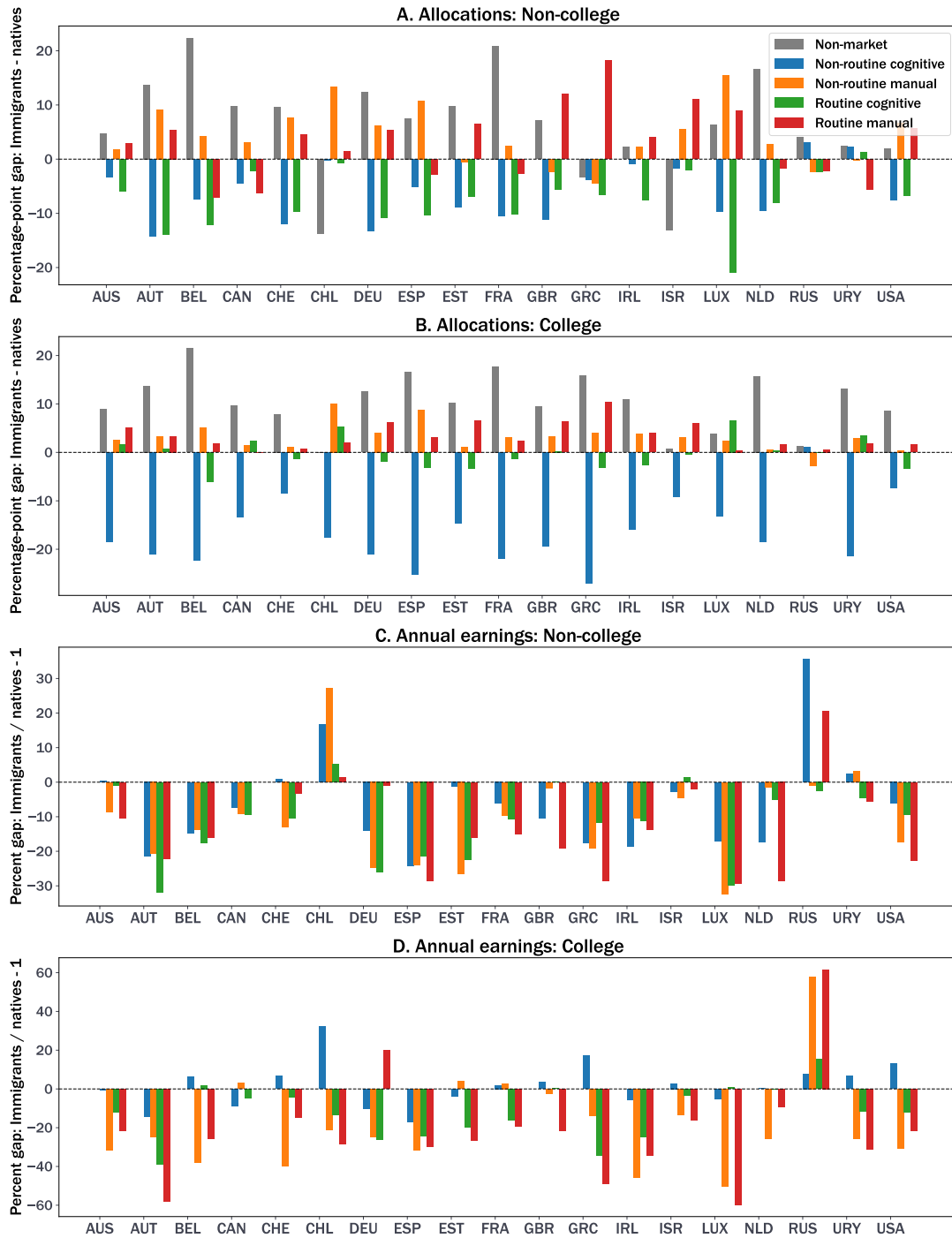
**Additional results.** In the main text, Figures 3 and 4 present cross-country differences in allocations and annual earnings between all immigrants and natives. Here, we first provide cross-country differences in hourly wages between all immigrants and natives in Figure A1. We find that the average hourly wage gaps between immigrants and natives across occupations are similar to annual earnings gaps presented in Figure 4. In particular, we find that the average hourly wages of immigrants are (i) larger than those of natives in non-routine cognitive occupations in around half of the countries in our sample, and (ii) lower than those of natives in non-routine manual, routine cognitive, and routine manual occupations in almost all countries. Moreover, we also find that magnitudes of these hourly wage gaps between immigrants and natives across occupations vary significantly across countries.

Figure A2: Allocations and annual earnings between immigrants and natives: Gender



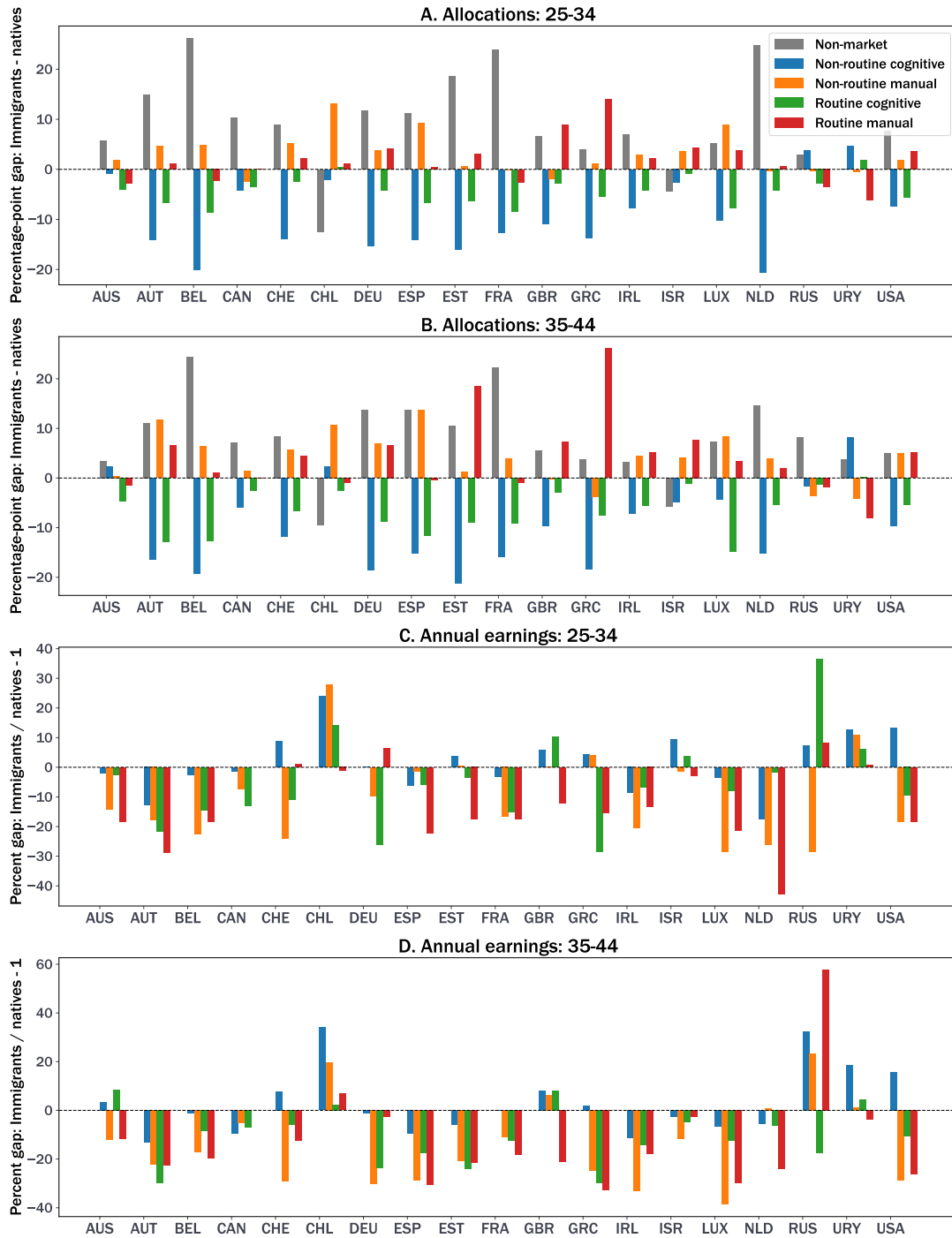
*Notes:* This figure presents differences by gender in labor market allocations and annual earnings between immigrants and natives across countries. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average annual earnings of immigrants and natives in each occupation. Panels A and B show the percentage-point gap (calculated as immigrants – natives) between fractions of immigrants and natives in each occupation across countries separately for males and females, respectively. Panels C and D show the percent gap (calculated as immigrants/natives – 1) between annual earnings of immigrants and natives in each occupation across countries for the same gender groups, respectively. Harmonized data on immigration status, employment, earnings, and demographics are obtained from the LIS database.

Figure A3: Allocations and annual earnings between immigrants and natives: Education



*Notes:* This figure presents differences by education in the labor market allocations and annual earnings between immigrants and natives across countries. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average annual earnings of immigrants and natives in each occupation. Panels A and B show the percentage-point gap (calculated as immigrants – natives) between fractions of immigrants and natives in each occupation across countries separately for individuals without a college degree and with a college degree, respectively. Panels C and D show the percent gap (calculated as immigrants/natives – 1) between annual earnings of immigrants and natives in each occupation across countries for the same education groups, respectively. Harmonized data on immigration status, employment, earnings, and demographics are obtained from the LIS database.

Figure A4: Allocations and annual earnings between immigrants and natives: Age



*Notes:* This figure presents differences in labor market allocations and annual earnings between immigrants and natives across countries for different age groups. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average annual earnings of immigrants and natives in each occupation. Panel A and B show the percentage-point gap (calculated as immigrants – natives) between fractions of immigrants and natives in each occupation across countries separately for individuals of ages between 25 and 34 and 35 and 44, respectively. Panels C and D show the percent gap (calculated as immigrants/natives – 1) between annual earnings of immigrants and natives in each occupation across countries for the same age groups. Harmonized data on immigration status, employment, earnings, and demographics are obtained from the LIS database.

Next, in Figures A2, A3, and A4, we document how allocations and annual earnings gaps between immigrants and natives in various gender, education, and age groups differ across countries, respectively.<sup>6</sup> We highlight the following observations. First, in the U.S., the fraction of male immigrants in non-routine cognitive occupations is comparable to that of male natives. In contrast, the fraction of male immigrants in these occupations is significantly lower than that of male natives in most other countries. On the other hand, a salient feature across almost all countries is that there is a much larger fraction of female immigrants in the non-market occupation than female natives in that occupation. Second, in terms of annual earnings, the average earnings of immigrants with or without a college degree are typically lower than their native counterparts across all occupations in almost all countries. Finally, we also find that life-cycle effects impact the earnings gaps between immigrants and natives differently across countries. For instance, in the Netherlands, the average earnings of immigrants between ages 25 and 34 are lower in non-routine cognitive occupations than those of natives in the same age group. This gap becomes smaller for individuals between ages 35 and 44. However, in Germany, immigrants between ages 25 and 34 also earn less than natives in this age group in non-routine manual occupations and this gap widens further for individuals between ages 35 and 44. These findings emphasize the importance of accounting for demographic differences between immigrants and natives across countries when estimating the model.

## C Estimation

This section provides derivations of model equations used in Section 3 when estimating the model. We then provide additional results in relation to our discussions in Section 3.

### C.1 Derivations

We first present the derivation of Equations (1)-(5) in the paper.

**Preliminaries.** Our derivation of these equations relies on a few auxiliary results that are used throughout. The derivation of these auxiliary results is standard—for further details on some of these, see the appendix of Hsieh et al. (2019).

First, we have that the probability that workers (type, subtype)  $(i, g)$  choose occupation  $j = 0, \dots, J$  is given by:

$$p_{ig}^j = \frac{[(1 + \gamma_{ig}^j)\nu_g^j (1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig}^j]^\eta}{\sum_{q=0}^J [(1 + \gamma_{ig}^q)\nu_g^q (1 - \tau_g^q - \kappa_{ig}^q) w_{ig}^q z_{ig}^q]^\eta}.$$

Second, we have that the geometric average earnings of a worker (type, subtype)  $(i, g)$  in occupation  $j$  is given by:

---

<sup>6</sup>Results for hourly wage gaps are similar to those for annual earnings gaps.



$$\text{Earnings}_{ig}^j = [(1/p) (1 + \gamma_{ig}^j) \nu_g^j]^\xi [(1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig}^j (1 + s)]^{1+\xi} \left( \frac{1}{p_{ig}^j} \right)^{\frac{1+\xi}{\eta}} \exp \left[ \frac{(1 + \xi) \gamma_{em}}{\eta} \right],$$

where  $\gamma_{em}$  is the Euler-Mascheroni constant.

Third, we have that the optimal labor demand in the inner nest of outer nest  $v$  in occupation  $j$  under perfect substitution is given by:

$$\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^j = \left( \frac{w_v^j}{p_j} \right)^{-\sigma_j} A_j^{\sigma_j - 1} y_j.$$

Fourth, we have that the demand for the goods produced in occupation  $j$  is:

$$y_j = \left( \frac{p_j}{p} \right)^{-\sigma} y.$$

Finally, we have that the labor market clearing condition for workers (type, subtype)  $(i, g)$  in market occupation  $j = 1, \dots, J$  can be expressed as:

$$n_{ig}^j = N_{ig} z_{ig}^j [(1/p)(1 + \gamma_{ig}^j) \nu_g^j (1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig}^j (1 + s)]^\xi (p_{ig}^j)^{\frac{\eta - (1+\xi)}{\eta}} \Gamma \left( 1 - \frac{1 + \xi}{\eta} \right).$$

**Equation 1.** Consider a pair (type, subtype)  $(i, g)$  and two alternative occupations  $j$  and  $k$ . The ratio of the geometric average earnings of these workers across the occupations is given by:

$$\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{ig}^k} = \frac{[(1 + \gamma_{ig}^j) \nu_g^j]^\xi [(1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig}^j]^{1+\xi} \left( \frac{p_{ig}^k}{p_{ig}^j} \right)^{\frac{1+\xi}{\eta}}}{[(1 + \gamma_{ig}^k) \nu_g^k]^\xi [(1 - \tau_g^k - \kappa_{ig}^k) w_{ig}^k z_{ig}^k]^{1+\xi} \left( \frac{p_{ig}^j}{p_{ig}^k} \right)^{\frac{1+\xi}{\eta}}}.$$

Plugging in the corresponding expressions for  $p_{ig}^j$  and  $p_{ig}^k$  and then simplifying, we obtain Equation (1):

$$\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{ig}^k} = \frac{(1 + \gamma_{ig}^k) \nu_g^k}{(1 + \gamma_{ig}^j) \nu_g^j}.$$

**Equation 2.** We derive Equation (2) by considering two worker (type, subtype) pairs  $(i, g)$  and  $(q, r)$  who choose a given occupation  $j$ :

$$\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{qr}^j} = \frac{[(1 + \gamma_{ig}^j) \nu_g^j]^\xi [(1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig}^j]^{1+\xi} \left( \frac{p_{qr}^j}{p_{ig}^j} \right)^{\frac{1+\xi}{\eta}}}{[(1 + \gamma_{qr}^j) \nu_r^j]^\xi [(1 - \tau_r^j - \kappa_{qr}^j) w_{qr}^j z_{qr}^j]^{1+\xi} \left( \frac{p_{ig}^j}{p_{qr}^j} \right)^{\frac{1+\xi}{\eta}}}.$$

We have that Equation (2) follows from setting  $j = 0$  and  $(q, r)$  to base (type, subtype) pair  $(b, m)$  given that (i) wages are equated across worker types in the non-market occupation, (ii) immigrant compensation and labor supply wedges are normalized to zero in occupation  $j = 0$ , (iii) common preferences are normalized to one and common compensation wedges are normalized to zero in occupation  $j = 0$ , (iv) productivity of base (type, subtype) in occupation  $j = 0$

is normalized to one, and ( $v$ ) earnings in the non-market occupation is set to a fraction  $\lambda$  of the weighted average of annual earnings across all market occupations for each (type, subtype).

**Equation 3.** We derive Equation (3) by considering a worker (type, subtype) ( $i, g$ ) and two alternative occupations  $j$  and  $k$ . Our starting point are the relative allocations within workers across occupations:

$$\frac{p_{ig}^j}{p_{ig}^k} = \left[ \frac{(1 + \gamma_{ig}^j) \nu_g^j \text{Wages}_{ig}^j z_{ig}^j}{(1 + \gamma_{ig}^k) \nu_g^k \text{Wages}_{ig}^k z_{ig}^k} \right]^\eta.$$

This expression follows from simplifying the ratio of probabilities  $p_{ig}^j$  presented earlier in this section. Setting  $k = 0$  and plugging Equation (1) we obtain the desired expression.

**Equation 4.** We derive Equation (4) by considering consider two outer nests  $v$  and  $q$  in a given occupation  $j$ .

The first part of the derivation consists of obtaining an expression for relative wages  $w_{ig}^j$  as a function of observables and/or parameters that can be backed out from observables up to this point. On the one hand, we compute the relative demand for labor across workers within occupations:

$$\frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^j}{\sum_{i \in \mathcal{I}_q} \sum_{g=1}^G n_{ig}^j} = \left( \frac{w_v^j}{w_q^j} \right)^{-\sigma_j}.$$

On the other hand, we use the market clearing conditions to compute the relative amount of labor across workers within occupations:

$$\frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^j}{\sum_{i \in \mathcal{I}_q} \sum_{g=1}^G n_{ig}^j} = \left( \frac{w_v^j}{w_q^j} \right)^\xi \frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G N_{ig} z_{ig}^j [(1 + \gamma_{ig}^j) \nu_g^j (1 - \tau_g^j - \kappa_{ig}^j) z_{ig}^j]^\xi (p_{ig}^j)^{\frac{\eta - (1 + \xi)}{\eta}}}{\sum_{i \in \mathcal{I}_q} \sum_{g=1}^G N_{ig} z_{ig}^j [(1 + \gamma_{ig}^j) \nu_g^j (1 - \tau_g^j - \kappa_{ig}^j) z_{ig}^j]^\xi (p_{ig}^j)^{\frac{\eta - (1 + \xi)}{\eta}}}.$$

Equating the left-hand side of these expressions, we solve for relative wages:

$$\frac{w_v^j}{w_q^j} = \left\{ \frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G N_{ig} z_{ig}^j [(1 + \gamma_{ig}^j) \nu_g^j \text{Wages}_{ig}^j z_{ig}^j]^\xi (p_{ig}^j)^{\frac{\eta - (1 + \xi)}{\eta}}}{\sum_{i \in \mathcal{I}_q} \sum_{g=1}^G N_{ig} z_{ig}^j [(1 + \gamma_{ig}^j) \nu_g^j \text{Wages}_{ig}^j z_{ig}^j]^\xi (p_{ig}^j)^{\frac{\eta - (1 + \xi)}{\eta}}} \right\}^{\frac{-1}{\sigma_j}}.$$

We plug this expression into the following expression that characterizes ratio of observed hourly wages:

$$\frac{\text{Wages}_{ig}^j}{\text{Wages}_{qr}^j} = \frac{(1 - \tau_g^j - \kappa_{ig}^j) w_{ig}^j}{(1 - \tau_r^j - \kappa_{qr}^j) w_{qr}^j}.$$

Equation (4) results from combining these expressions where we set  $q = 1$  (i.e., natives) which implies setting  $\kappa_{gr}^j = 0$  and dropping summations over  $i \in \mathcal{I}_q$  as there is only one native type (all natives).

**Equation 5.** Consider now the relative demand for labor across market occupations  $j$  and  $k$  within outer nest  $v$ :

$$\frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^j}{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^k} = \frac{\left(\frac{w_v^j}{p_j}\right)^{-\sigma_j} A_j^{\sigma_j-1} y_j}{\left(\frac{w_v^k}{p_k}\right)^{-\sigma_k} A_k^{\sigma_k-1} y_k}.$$

Plugging in the solution to the final good producer's problem, we obtain:

$$\frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^j}{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^k} = \frac{\left(\frac{w_v^j}{p_j}\right)^{-\sigma_j} A_j^{\sigma_j-1}}{\left(\frac{w_v^k}{p_k}\right)^{-\sigma_k} A_k^{\sigma_k-1}} \left(\frac{p_j}{p_k}\right)^{-\sigma}.$$

Let  $\sigma_j = \sigma_k = \sigma$  for all  $j$  and  $k$ . Then, the expression can be simplified to obtain:

$$A_j = \left\{ \left(\frac{w_v^j}{w_v^k}\right)^\sigma A_k^{\sigma-1} \frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^j}{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G n_{ig}^k} \right\}^{\frac{1}{\sigma-1}}.$$

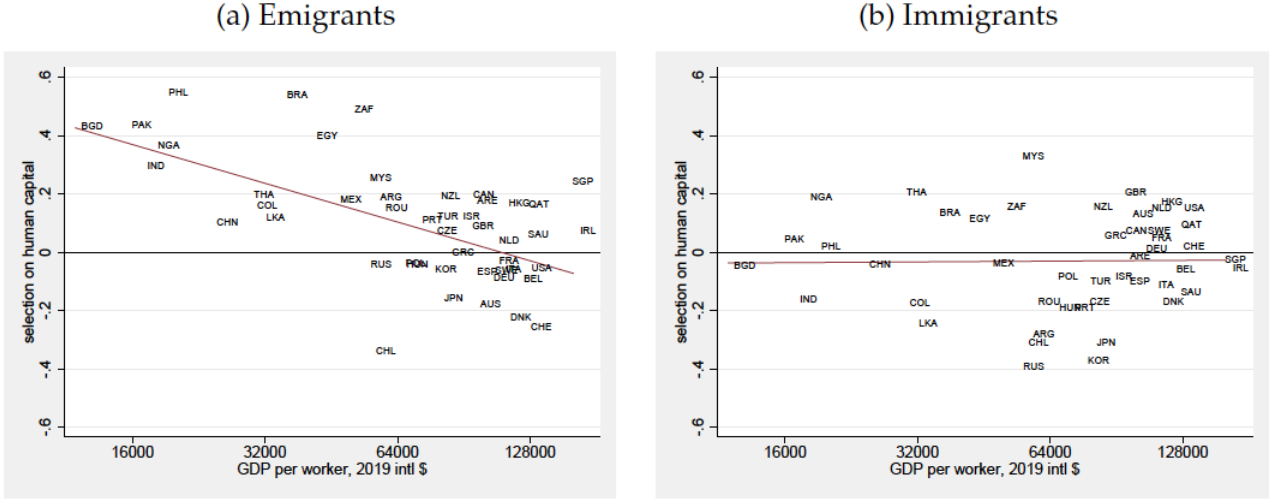
Then, we obtain Equation (5) by implementing the following steps: (i) plug in the respective labor market clearing conditions, (ii) substitute the wage ratio used in the last step of the derivation of Equation (4), (iii) set  $k = 1$  with normalization  $A_1 = 1$ , and (iv) write the equation for base (type, subtype)  $(b, m)$  (and dropping summations over  $i \in \mathcal{I}_v$  as the base type is natives and there is only one native type) and simplify.

## C.2 Additional results

**Average human capital across immigrants, emigrants, and non-migrants.** In Section 3.2, in order to discipline the shape parameter  $\eta_i$  of the Frechet distribution of idiosyncratic productivities across immigrants and natives, we provide a discussion on empirical findings in [Martellini, Schoellman, and Sockin \(2023\)](#). Here, Figure A5 is copied from [Martellini, Schoellman, and Sockin \(2023\)](#) to provide ease of reference. For each country  $c$ , Panel (a) shows the log difference in average human capital for emigrants from  $c$  as compared to non-migrants. Panel (b) shows the same for immigrants to  $c$  relative to non-migrants. Countries are ordered in PPP GDP per worker (in log scale) in horizontal axis of both figures. For more details, please refer to [Martellini, Schoellman, and Sockin \(2023\)](#).

**Estimation results.** Table A2 shows the model counterparts of the empirical moments presented in Table 1. Overall, the model closely matches the empirical moments in Table 1.

Figure A5: Average human capital of emigrants and immigrants relative to non-migrants



Source: [Martellini, Schoellman, and Sockin \(2023\)](#)

*Notes:* This figure is copied from [Martellini, Schoellman, and Sockin \(2023\)](#) to provide ease of reference. For each country  $c$ , Panel (a) shows the log difference in average human capital for emigrants from  $c$  as compared to non-migrants. Panel (b) shows the same for immigrants to  $c$  relative to non-migrants. Countries are ordered in PPP GDP per worker (in log scale) in horizontal axis of both figures. For more details, please refer to [Martellini, Schoellman, and Sockin \(2023\)](#).

## D Additional Results

In this section, we provide additional results to complement our discussions in Section 4.

**Quantitative significance of aggregate gains from removing immigrant wedges.** In Section 4.2, we discuss an exercise to evaluate the quantitative significance of our findings on the aggregate real GDP gains from removing immigrant wedges. In this section, we provide more details about this exercise and present the results.

When evaluating the quantitative significance of our findings, we need to confront the observation that the aggregate effects of removing immigrant wedges are naturally a function of the share of immigrants in the economy. If immigrants are few, then mechanically the effects will be estimated to be modest even if the distortions are substantial. Thus, we put our findings in context by comparing the effects from removing immigrant wedges to the overall contribution of immigrants to the U.S. economy. We compute the contribution of immigrants in the U.S. by comparing the baseline model with a counterfactual economy without immigrants, which we solve by setting the mass of immigrants to zero.

Table A3 reports the value of real GDP, TFP, employment, and average hours worked for three economies: the economy without immigrants (no immigrants), the baseline economy (the economy with immigrants and immigrant wedges), and the economy with immigrants but without immigrant wedges examined above (no immigrant wedges). We find that the real GDP gains from immigration are equal to 28.2% relative to an economy without immigrants ( $1/0.78$ ). This

Table A2: Estimation results for distribution, annual earnings, and hourly wages

Occupation type	Distribution						
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>
Non-routine cognitive	0.32	0.26	0.25	0.02	0.34	0.36	0.44
Non-routine manual	0.11	0.19	0.18	0.23	0.15	0.16	0.10
Routine cognitive	0.19	0.11	0.14	0.05	0.15	0.14	0.16
Routine manual	0.16	0.20	0.24	0.36	0.18	0.15	0.10
Non-market	0.22	0.25	0.20	0.34	0.18	0.19	0.20
Occupation type	Annual earnings						
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>
Non-routine cognitive	1.75	1.88	2.17	1.23	2.12	2.18	2.41
Non-routine manual	0.75	0.55	0.68	0.48	0.71	0.67	0.81
Routine cognitive	1.03	0.81	1.01	0.61	1.01	0.94	1.28
Routine manual	1.06	0.74	0.93	0.62	1.00	0.94	1.32
Occupation type	Hourly wages						
	N	I <sub>0-10</sub>	I <sub>10+</sub>	I <sub>Low Eng</sub>	I <sub>High Eng</sub>	I <sub>LIC</sub>	I <sub>HIC</sub>
Non-routine cognitive	1.75	1.88	2.17	1.23	2.12	2.18	2.41
Non-routine manual	0.75	0.55	0.68	0.48	0.71	0.67	0.81
Routine cognitive	1.03	0.81	1.01	0.61	1.01	0.94	1.28
Routine manual	1.06	0.74	0.93	0.62	1.00	0.94	1.32

*Notes:* This table presents model-implied targeted moments for the allocation of individual types as well as their annual earnings and hourly wages across occupations. We first calculate the outcomes for each individual (type, subtype) pair in each 25 occupation. For expositional purposes, we report the average moments for natives and immigrant types across four broad occupation categories, where we assign 25 market occupations into categories based on their skill and task-intensity: non-routine cognitive, non-routine manual, routine cognitive, and routine manual. The distribution of individuals across occupations is conditional on each worker type. Annual earnings and hourly wages are expressed relative to respective values for the base native subtype and occupation: native males of ages 25 to 34 without high school degree and employed in management, business, science, and arts occupations.  $N$  denotes natives,  $I_{0-10}$  denotes recent immigrants ( $\leq 10$  years),  $I_{10+}$  denotes established immigrants ( $>10$  years),  $I_{Low Eng}$  denotes low English proficiency immigrants,  $I_{High Eng}$  denotes high English proficiency immigrants,  $I_{LIC}$  denotes immigrants originating from low-income countries, and  $I_{HIC}$  denotes immigrants originating from high-income countries.

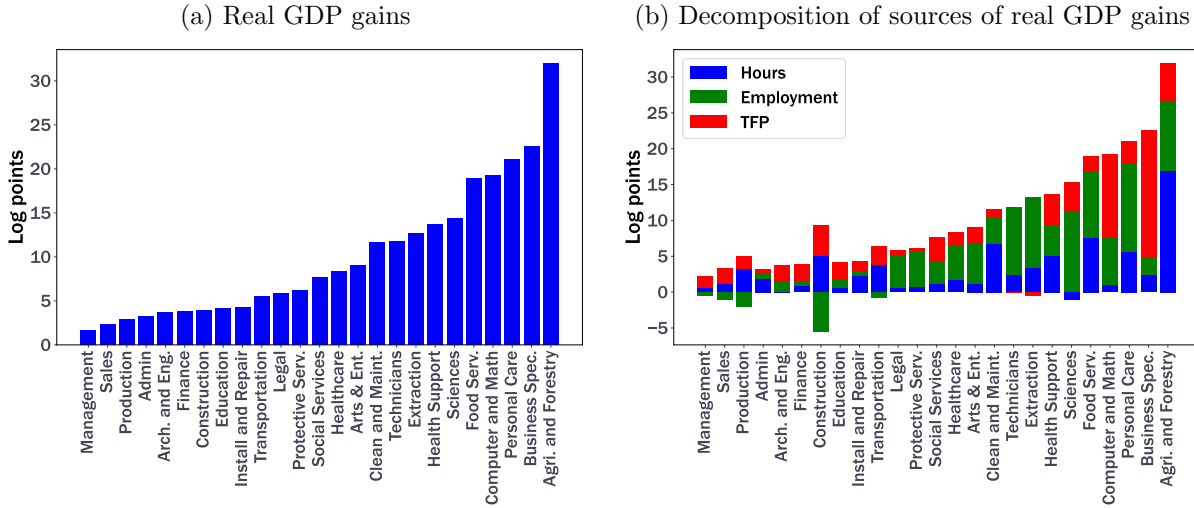
Table A3: Gains from removing immigrant barriers vs. gains from immigration

	Real GDP	TFP	Employment	Hours
No immigrants	0.78	0.98	0.80	0.99
Baseline	1.00	1.00	1.00	1.00
No immigrant wedges	1.07	1.02	1.02	1.02
Gains ratio	24.8			

*Notes:* This table presents a comparison of real GDP, TFP, employment, and average hours worked under three scenarios: (i) the economy without immigrants (no immigrants), (ii) the baseline economy (the economy with immigrants and immigrant wedges), and (iii) the economy with immigrants but without immigrant wedges examined above (no immigrant wedges).

implies that the real GDP gains from removing immigrant wedges are 24.8% of the total gains from immigration (6.98/28.2). Hence, we conclude that immigrants' current contribution to the

Figure A6: Real GDP gains and sources of real GDP gains across all market occupations



Notes: Panel (a) plots real GDP gains from removing immigrant wedges across all market occupations and Panel (b) provides a decomposition of contribution of TFP, employment, and average hours changes to total real GDP gains across these occupations.

U.S. economy would increase by 24.8% in the absence of immigrant wedges.

**Effects of removing immigrant wedges across all occupations.** Table 4 in Section 4.2 analyzes the effects of removing immigrant wedges across occupations, where we grouped occupations into four broad task-based occupation categories for expositional purposes. Here, we now provide results across all 26 occupations in our analysis.

Panel (a) in Figure A6 provides real GDP gains from removing immigrant wedges across all market occupations. We find that gains are highest in farming, fishing (agriculture), and forestry occupation and lowest in management, business, science, and arts (management) occupations. Overall, we find that highest real GDP gains are typically in non-routine occupations, while lowest real GDP gains are typically in routine occupations.

Panel (b) in Figure A6 provides a decomposition of real GDP gains due to changes in TFP, employment, and average hours worked across market occupations. Among occupations with highest real GDP gains, we find that increases in employment are typically the major source behind these gains, except agriculture and forestry, business, and computer and mathematical occupations. In agriculture and forestry the increase in average hours worked is the main driver of real GDP gains, while increases in TFP are the primary source behind real GDP gains in business, and computer and mathematical occupations. On the other hand, among occupations with lowest real GDP gains, we find much smaller employment gains. In these occupations, around half of real GDP gains are typically accounted for by increases in TFP.

**Removing immigrant wedges for each immigrant type/subtype.** Table 6 in Section 4.3 presents the gains associated with removing immigrant wedges faced by specific immigrant types

Table A4: Reallocation arising from removing wedges by immigrant type/subtype

Wedges removed	Mass of subtype (% change)	Non-routine cognitive	Non-routine manual	Routine cognitive	Routine manual	Non-market
By age						
25-34	25-34	23.58	25.14	-1.32	-10.41	-34.20
	35-44	-0.33	-0.54	0.21	0.10	0.65
	45-54	-0.34	-0.50	0.24	0.06	0.68
35-44	25-34	-0.77	-0.79	0.40	0.15	1.06
	35-44	20.98	26.72	-2.69	-5.49	-42.53
	45-54	-0.55	-0.81	0.35	0.18	1.02
45-54	25-34	-0.15	-1.24	0.06	0.05	1.00
	35-44	-0.08	-1.20	0.06	0.07	1.03
	45-54	8.37	33.98	6.95	-2.21	-45.04
By degree						
Less than high school	Less than high school	312.72	27.12	16.49	-10.69	-46.81
	High school	-0.70	-0.69	0.17	0.13	0.74
	Less than college	-0.66	-0.60	0.25	0.29	0.80
	College	-0.54	-0.28	0.70	0.78	1.22
High school	Less than high school	-0.37	-0.96	0.02	0.18	0.67
	High school	94.83	33.99	0.77	-13.21	-53.68
	Less than college	-0.39	-1.16	0.32	0.26	1.01
	College	-0.23	-1.17	0.29	0.29	0.96
Less than college	Less than high school	-0.19	-0.35	-0.12	-0.06	0.46
	High school	-0.14	-0.42	-0.05	0.00	0.56
	Less than college	19.57	21.03	0.03	3.03	-46.00
	College	-0.12	-0.57	0.00	0.09	0.60
College	Less than high school	0.10	-0.45	0.18	-0.09	0.49
	High school	-0.08	-0.52	0.14	0.03	0.49
	Less than college	-0.24	-0.52	0.14	0.08	0.56
	College	-0.62	34.40	-6.21	31.85	-16.95

*Notes:* This table presents the percent changes in the masses of immigrants allocated to market and non-market occupations arising from the removal of immigrant distortions for a specific immigrant type or subtype. The first column refers to the subtype of immigrants for whom distortions are removed in the counterfactual, while the second column refers to the subtype of immigrants for whom changes in the occupational distribution are being presented.

or subtypes. In order to provide further intuition for the results in Table 6, Table A4 presents the percent change in the mass of immigrants across market and non-market occupations under selected counterfactual economies wherein immigrant distortions for a specific immigrant type or subtype is removed. For example, the first three rows pertain to changes in the distribution

Table A5: Gains from removing immigrant wedges by occupation

Occupation type	Real GDP	Share of population	Real GDP growth
	(% change)	(baseline level, %)	per 1% of imm. (%)
Non-routine cognitive	5.11	4.82	1.06
Non-routine manual	0.38	3.43	0.11
Routine cognitive	0.84	2.44	0.34
Routine manual	0.99	4.25	0.23

*Notes:* This table presents the effects of removing immigrant wedges by occupation on real GDP. We note that we implement this exercise by removing wedges for each of the 25 market occupations separately, but present results in this table by four broad occupation categories for expositional purposes. The first column presents the percent change in real GDP when immigrant wedges in a given occupation are removed relative to the baseline economy. The second column presents the share of immigrants in each occupation in the total population. Finally, the third column presents the ratio of real GDP growth (column 1) to the share of each occupation in the economy (column 2) to adjust for heterogeneity in the mass of individuals across occupations.

of immigrants in three categories of age across occupations under an economy where distortions for immigrants of ages between 25 and 34 are removed. A discussion of the results presented in Table A4 is provided around Table 6 in the main text.

**Removing immigrant wedges for each occupation.** In Section 4.3, we briefly mention results on the degree of heterogeneity in real GDP gains from removing immigrant wedges across occupations. Here, we provide these results in detail.

Table A5 presents the gains from removing immigrant wedges by occupation. To do so, for each of the 25 market occupations  $j$ , we examine the impact of removing the immigrant wedges of all immigrants in occupation  $j$  while keeping wedges in other occupations unchanged.<sup>7</sup> Table A5 shows that real GDP gains per immigrant from removing immigrant barriers are highest when these barriers are removed in non-routine cognitive occupations and lowest when they are removed in non-routine manual occupations.

## E Results under Alternative Parametrizations

In this section, we provide our main results on changes in aggregate real GDP, TFP, employment, and hours worked when immigrant wedges are removed under alternative parametrizations of our baseline model using the ACS, as mentioned in Section 8. We consider (i) alternative production technologies that differ in how labor bundles are aggregated across worker types and subtypes (e.g., different nesting, as well as different elasticities), and (ii) alternative values for other predetermined parameters. In each of these cases, we re-estimate the model's parameters and wedges and then compute changes in aggregate real GDP, TFP, employment, and hours worked when immigrant wedges are removed. These results are summarized in Table A6. Overall, our main results remain similar to our baseline results with two intuitive exceptions: A lower

<sup>7</sup>We note that we implement this exercise by removing wedges for each of the 25 market occupations separately, but present results in this table by four broad occupation categories for expositional purposes.



Table A6: Gains from removing immigrant wedges under alternative parametrizations

	Percent change				Change in immigrant share (pp)
	Real GDP	TFP	Employment	Hours	
Baseline	6.98	2.48	1.91	2.43	1.62
Elasticity of substitution between natives and immigrants with $\sigma_j = 4.6$	11.86	4.92	2.93	3.58	2.99
Imperfect substitution across natives and all immigrant types	8.86	2.76	3.08	2.77	2.61
Imperfect substitution between education groups	7.11	2.50	1.95	2.50	1.65
Perfect substitution across natives and all immigrant types	6.37	2.22	1.67	2.34	1.37
Higher value for elasticity of substitution across subtypes in inner nest	7.21	2.40	2.25	2.39	1.89
25 percent UI replacement rate, $\lambda = 0.25$	6.90	2.49	1.91	2.34	1.62
75 percent UI replacement rate, $\lambda = 0.75$	7.04	2.46	1.91	2.51	1.62

*Notes:* This table presents the percent change in aggregate real GDP, TFP, employment, and hours when immigrant wedges are set equal to their counterpart natives of the same subtype under alternative values of model parameters. Please refer to main text for a detailed discussion on these exercises.

substitutability of labor bundles between natives and all immigrants or a lower substitutability of labor bundles across different immigrant types leads to larger gains from removing immigrant wedges. Below, we provide details about these exercises.

First, in Section 3.2, following [Ottaviano and Peri \(2012\)](#), we set the elasticity of substitution between natives and immigrants in the outer nest to  $\sigma_j = 20 \quad \forall j = 1, \dots, J$ . While this is their preferred estimate when the native-immigrant elasticity is restricted to be the same for all education groups as in our baseline estimation, we acknowledge that there are alternative values used across different studies. For this reason, we present our main results under  $\sigma_j = 4.6 \quad \forall j = 1, \dots, J$  as in [Burstein, Hanson, Tian, and Vogel \(2020\)](#). Intuitively, when immigrant and native labor bundles are much less substitutable, real GDP gains from removing immigrant wedges becomes much larger, increasing to 11.86% from its baseline value of 6.98%.

Second, in our model, we assume that the outer nest aggregates labor bundles of natives and all types of immigrants (without taking into account different immigrant types). Here, we make a change to the production technology so that the outer nest aggregates worker bundles of natives and all 18 types of immigrants (i.e., an aggregation across 19 worker bundles instead of 2 in the baseline specification). Recall that, in Section 3.3, we assume that labor bundles in the outer nest are imperfect substitutes, while labor bundles in the inner nest are perfect substitutes. Thus, the implication of this change in the production technology is that immigrants of different types now become imperfectly substitutable. This captures the possibility that immigrants with different characteristics based on time since arrival, fluency in English, and the income level of country of origin may be imperfectly substitutable. As Table A6 shows, when these types of immigrants are imperfect substitutes, real GDP gains from removing immigrant wedges are larger. This exercise shows that our baseline specification where all immigrant types are perfect substitutes sets a lower bar for gains from removing wedges. When all types of immigrants are imperfect substitutes, our framework predicts much larger gains from removing wedges.

Third, we make another change to the production technology such that individuals with

different education levels are imperfect substitutes. Specifically, the outer nest now aggregates worker bundles between natives with a college degree, natives without a college degree, immigrants with a college degree, and immigrants without a college degree. We find that this change in the production technology does not largely alter our main results.

Fourth, we check our main results when we assume perfect substitution between labor bundles in the outer nest that aggregates labor bundles of natives and all types of immigrants. We approximate perfect substitution in the outer nest with  $\sigma_j = 40 \forall j = 1, \dots, J$ , the same value we use to approximate perfect substitution in the inner nest with  $\tilde{\sigma}_j = 40 \forall j = 1, \dots, J$ . Because our baseline calibration with  $\sigma_j = 20 \forall j = 1, \dots, J$  already assumes a large degree of substitutability across immigrant and native labor bundles in the outer nest, our results do not significantly change when we instead assume  $\sigma_j = 40 \forall j = 1, \dots, J$ .

Fifth, in our estimation, we approximate the perfect substitution across labor bundles in the inner nest with  $\tilde{\sigma}_j = 40 \forall j = 1, \dots, J$ . Table A6 shows that our results remain similar under a higher value of this elasticity (i.e.,  $\tilde{\sigma}_j = 80 \forall j = 1, \dots, J$ ).

Finally, for each individual (type, subtype) pair, we set annual earnings in the non-market occupation to be 50 percent of the weighted average annual earnings across all market occupations, i.e.,  $\lambda = 0.5$ . We find that using alternative values, i.e.,  $\lambda = 0.25$  or  $\lambda = 0.75$ , does not largely alter our results.