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Authors	Serdar Birinci, Fernando Leibovici, and Kurt See
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Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

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

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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, Leibovici: fleibovici@gmail.com, See: kurtgerrardsee@gmail.com. We thank Pete Klenow, Joan Llull, Joan Monras, Todd Schoellman, Ayşegül Şahin, and 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 Jennifer Bernstein 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

Immigration policy is central to economic and political debates in developed countries, especially amid labor shortages and aging populations. While much attention is given to how many immigrants are admitted and who they are, far less is devoted to how effectively they integrate into labor markets. Key barriers—such as occupational licensing, unrecognized foreign credentials, language constraints, and discrimination—are often overlooked, despite their potential to reduce economic gains from immigration. Although some of these barriers are documented individually at the micro level, their combined macroeconomic implications remain less well understood. This paper quantifies the aggregate economic costs of barriers to immigrant labor market integration.

Importantly, these barriers have a direct role in shaping the macroeconomic effects of immigration. A separate, long-standing body of research studies how immigration affects various macroeconomic outcomes (e.g., Borjas, 1995; Llull, 2018; Monras, 2020; Albert and Monras, 2022; Monras, Vázquez-Grenno, and Elias, 2022), often without accounting for the role of immigrant labor market barriers. Yet, the macroeconomic effects of immigration depend not only on who enters the labor force but also on how effectively immigrants are employed. Constraints on immigrant occupational mobility and productivity can significantly reduce the gains from immigration, while removing these barriers through policy can enhance their economic contributions.

Our main contribution is to combine micro-level studies on the measurement of specific labor market barriers faced by immigrants and macro-level analysis on the effects of immigration in order to provide a unified framework for (*i*) quantifying the *joint* macroeconomic effects of immigrant barriers, (*ii*) assessing how they shape the economic impact of immigration, and (*iii*) analyzing their effects on the outcomes of immigration policies. To do so, we develop an occupational choice model for natives and immigrants that takes into account two key elements critical to quantifying the effects of immigration. First, we account for labor market barriers that prevent immigrants from working in the occupations where they would be most productive, causing a misallocation of immigrant talent and, ultimately, constraining their potential contribution to the economy. Second, we differentiate immigrants along relevant dimensions of heterogeneity, including education, language ability, country of origin, and time since immigration. This is key because the impact of immigration on the economy depends on the characteristics of the immigrants admitted. When immigrants have skills similar to natives and are highly substitutable, their economic contribution may be limited (Borjas, 1995). Applying this framework to harmonized microdata from 19 developed economies, we document new evidence on the magnitude and distribution of immigrant barriers across characteristics, occupations, and countries. We then quantify the macroeconomic gains from reducing these barriers, identify the channels through which they arise, and examine how barriers influence the effects of immigration policy.

We highlight four key findings that advance our understanding of immigrant barriers and their macroeconomic impact. First, immigrant barriers in the U.S. are sizable and vary across occupations and immigrant characteristics. Second, reducing barriers has large aggregate effects. Lowering barriers for all immigrants to the level faced by natives would increase real GDP by 7%, equivalent to 25% of immigrants' total economic contribution. Reducing barriers for recent immigrants alone yields a 3.4% gain. These gains are driven by higher employment, moving from routine to non-routine jobs, and higher hours. Third, immigrant barriers are widespread across countries and often exceed those in the U.S. Even countries with similar average barrier levels can realize different gains from reducing them, depending on immigrant unemployment rates and how barriers are distributed across occupations. Fourth, immigrant barriers alter the effects of immigration policies. In particular, the ranking of productivity gains from admitting new immigrants from different backgrounds changes markedly in the absence of immigrant barriers.

Our starting point is an equilibrium model populated by natives and immigrants. The model extends the framework developed by Hsieh et al. (2019) by modeling immigrants as in Burstein et al. (2020), and by introducing endogenous labor supply. We consider an 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. We characterize each worker group (partitioned based on native and immigrant characteristics as well as demographics) by a productivity level in each occupation. Thus, we allow the productivity of immigrants and natives to differ across occupations. Each individual also draws *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. Second, the production of occupation-specific goods features imperfect substitution between native and immigrant workers.

We derive analytical expressions to characterize the efficient allocation in our model. This benchmark corresponds to a case in which immigrant-specific wedges are eliminated and both natives and immigrants face identical distortions across occupations. In this benchmark, individuals of the same observable type should (i) earn the same average hourly wages in any occupation and (ii) have the same native-immigrant gap in average annual earnings across all occupations. These conditions provide a clear theoretical benchmark against which to assess any observed disparities in labor market outcomes between natives and immigrants across occupations.

Next, we empirically characterize these disparities by documenting key patterns of the joint distribution of employment, annual earnings, and hourly wages across individuals and occupations in the U.S. Using microdata from the American Community Survey (ACS), we identify substantial differences between natives and immigrants, as well as across immigrant groups. We classify immigrants based on time since immigration, English proficiency, and the income level of their origin country, while further partitioning both natives and immigrants by education, age, and gender. We allocate individuals between a non-market (non-employment) occupation and 25 market occupations. Our empirical findings reveal large deviations from the efficient benchmark, as immigrants with similar observable characteristics to natives experience large gaps in labor market outcomes across occupations, signaling the presence of immigrant-specific distortions.

To determine whether observed differences in immigrant labor market outcomes reflect differences in productivity or the presence of immigrant-specific barriers, we build on insights from Hsieh et al. (2019) and develop a strategy to disentangle them. Our model links individuals' choices and earnings to three underlying forces: how productive they are in each occupation, how desirable different occupations are to them, and how much they are paid once employed. This structure allows us to separately identify three key components—productivity, immigrant labor supply wedges, and immigrant compensation wedges—using data on occupational allocations, average earnings, and hourly wages. We begin by identifying immigrant labor supply wedges, which capture systematic differences in how attractive different occupations are to immigrants relative to observationally similar natives. These are recovered by comparing how immigrant earnings vary across occupations relative to natives, where the model structure implies that such differences are informative about utility—rather than productivity or pay—once wages and occupational choices are jointly considered. Next, we identify productivity using within-immigrant variation in annual earnings, hourly wages, and occupational choices. More productive immigrants tend to sort into certain occupations and earn more over the year relative to their hourly wage, allowing us to infer productivity from these patterns. Finally, we back out immigrant compensation wedges by comparing hourly wages of immigrants and natives within the same occupation, after accounting for productivity and selection.

Using our identification strategy, we back out wedges given a very limited set of predetermined parameters and widely accessible data. 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. This approach ensures the estimation of the model with rich heterogeneity and delivers insights on data patterns that identify wedges and productivities. We find that the estimated immigrant wedges and differences in productivities between natives and immigrants are sizable and vary across immigrant types and occupations. For instance, recent immigrants with lower English proficiency and who originate from low-income countries tend to be more productive than natives in manual occupations, yet these immigrants also face the largest wedges in these 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 reduced—that is, immigrants face the same level of distortions as natives across occupations. We find that reducing wedges for all immigrants increases real GDP by 7%, while reducing them only for recent immigrants increases it by 3.4%. 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. We note that these gains should be considered an upper bound, as we do not model the costs involved in reducing wedges, some of which (such as social or cultural norms) may not be easily eliminated.

We show that the gains from reducing immigrant wedges are heterogeneous across occupations and worker groups. Across occupations, the largest gains are seen in non-routine occupations, while the smallest gains are in routine occupations. Across immigrant types, we find that reduced immigrant wedges lead disadvantaged immigrant groups, such as recent immigrants or those with less education or English fluency, to be 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 reducing only the wedges faced by a particular immigrant group, we find that larger aggregate output gains are achieved when wedges are reduced for these disadvantaged immigrant groups. On the other hand, we identify much smaller aggregate gains when wedges are reduced 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. As a result, we show that accounting for rich heterogeneity in worker groups and occupations is pivotal in quantifying wedges and greatly amplifies the gains from their reduction.

A potential concern is that our estimated immigrant wedges may partly reflect unobserved productivity differences rather than genuine labor market barriers. We address this concern through a series of complementary validation and robustness exercises. First, we find that the magnitude of these wedges declines substantially with immigrants' time in the host country, consistent with the presence of barriers upon entry rather than permanent productivity differences. Second, we validate our wedge estimates against external evidence by documenting a strong positive correlation between the model-implied immigrant wedges and external measures of occupational licensing requirements in the U.S. Importantly, we find that these correlations are much higher when we compare licensing requirements with immigrant wedges for recent immigrants, but the correlations disappear for established immigrants. This result serves as additional validation of our estimates for immigrant wedges. If our estimates of immigrant wedges were to capture unobserved productivity differences between natives and immigrants, we would then expect correlations between model-implied wedges and licensing requirements to remain high as the time since arrival becomes longer. However, the disappearance of these correlations over time suggests that model-implied wedges capture barriers to work in occupations and that these barriers due to occupational licensing requirements lessen over time. In the latter part of the paper, we also leverage external cross-country measures of immigrant integration to validate model-implied wedges across countries in our sample. Third, we demonstrate the robustness of our main findings through alternative modeling assumptions that relate to immigrant productivity differences. In particular, we show that our key findings are robust when we relax the assumption of identical productivity distributions between natives and immigrants, and when we consider alternative mappings between productivity and observable outcomes in the data.

Given the pervasive and heterogeneous nature of immigrant barriers, we then investigate how these barriers affect the outcomes of immigration policies. In particular, we study the effects of increasing the mass of immigrants in the U.S. through the entry of new immigrants with alternative sets of characteristics. Importantly, we show that admitting new immigrants in an economy with lower immigrant barriers 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 also reduced upon admission. Thus, we conclude that the presence of wedges affects which immigrant groups should be prioritized when expanding immigration.

A key advantage of our approach is that our analysis for the U.S. can be easily extended to many countries given micro-level data on labor market outcomes and demographics of immigrants and natives. Extending our analysis across countries is valuable, as cross-sectional variation in labor market outcomes in the data and estimated immigrant wedges in the model help us further characterize the underlying channels through which immigrant barriers distort labor market outcomes. As a first step, we make an important empirical contribution by constructing harmonized target moments on the joint distribution of employment, annual earnings, and hourly wages across occupations for 19 countries using the Luxembourg Income Study (LIS) database. We then use these moments to document how the size and distribution of immigrant wedges vary across countries. Our findings highlight large heterogeneity in the size of the barriers across countries. For instance, countries such as the U.K. and Australia are estimated to feature both low immigrant wedges and gains from their reduction, 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 reducing them that are close to the average across the countries in our sample.

We find non-trivial heterogeneity in gains from reducing immigrant barriers, even across countries with similar average wedges. This cross-country variation can be traced to two key factors. On the extensive margin, countries with a higher share of non-employed immigrants experience larger gains from reducing wedges. On the intensive margin, gains are larger in economies where higher-productivity occupations or individuals are subject to larger wedges.

We conclude our cross-country analysis by comparing model-implied wedges with international measures of immigrant integration. Specifically, we focus on two indices that capture de facto barriers, reflected in public attitudes, and de jure barriers, reflected in government policies. Our estimated immigrant wedges align with these indices, as countries with more favorable attitudes or policies toward immigrants tend to 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; Hanson and Liu 2021; Piyapromdee 2021; Albert and Monras 2022; Monras, Vázquez-Grenno, and Elias, 2022). These papers develop models that are disciplined using microdata to analyze the impact of immigration on wages, migration, inequality, output, and welfare. We contribute to this literature by documenting differences in labor market outcomes between natives and immigrants of various types across occupations in different countries, and by using these empirical findings in our model 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.

This paper also contributes to a literature that studies differences in the labor market outcomes of natives and immigrants. Immigrants have been documented to be at a disadvantage in labor markets due to occupational regulations and licensing (Peterson et al. 2014), lower bargaining power against employers (Moreno-Galbis and Tritah 2016), discrimination (Oreopoulos 2011), and downgrading of skills (Eckstein and Weiss 2004; Dustmann et al. 2013). These barriers lead to immigrants' poorer labor market outcomes (Abramitzky and Boustan 2017; Arellano-Bover and San 2020; Dostie et al. 2020). Generally, most work in this literature explores one aspect of labor market barriers. Relative to the existing literature, our paper recovers the joint macroeconomic effect of immigrant barriers across a large number of 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.

The paper proceeds as follows. Section 2 presents the model. Section 3 details the data, estimation strategy, and identification. Section 4 reports U.S. estimation results. Section 5 examines policy implications of immigrant wedges. Section 6 extends the analysis to other countries. Section 7 assesses robustness under alternative model specifications. Section 8 concludes.

2 Model

In this section, we construct a static occupational choice model à 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), and by introducing endogenous labor supply. Relative to the former, our model lacks the dynamics, and relative to the latter, while our model differentiates immigrants along their language ability, origin country, time since immigration, and demographics, it does not account for regional differences.

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.

2.1 Individuals

Demographics. We consider a static model in which individuals live for one period. They are partitioned into types $i = 1, ..., I$ 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 $i = 2, ..., I$ denote the set of immigrant types. Individuals of every given type i are further partitioned into subtypes $g = 1, ..., G$ 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 ℓ units of labor to work in occupation $j = 0, ..., J$, 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 ξ denotes the Frisch elasticity, ν_g^j is a preference shifter that is common across all individuals of subtype g who work in occupation j, and γ_{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 γ 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 ℓ 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 ε_j is an idiosyncratic occupation-specific productivity draw.

Each individual of type i and subtype g is characterized by a vector of idiosyncratic productivities $(\varepsilon_0, ..., \varepsilon_J)$ for each of the occupations. These productivities are distributed Frechet with type-specific shape parameter η_i and *i.i.d.* across individuals and occupations, as in McFadden (1972), Eaton and Kortum (2002), and Hsieh et al. (2019). The joint CDF is thus given by $F(\varepsilon_0, ..., \varepsilon_j) = \exp\left(-\sum_{j=0}^{J}\varepsilon_j^{-\eta_i}\right)$. We model η_i as type-specific to capture other sources of productivity differences between natives and immigrants that are not modeled explicitly. These sources could include selection (Hendricks and Schoellman, 2018) or unobserved heterogeneity (e.g., due to differences in education quality across origin countries 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 et al., 2018b) across 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 τ_g^j. Immigrants of type $i = 2, ..., I$ are additionally subject to "immigrant compensation wedges" κ_{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.

We model two sources of immigrant barriers (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 captures 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 $(\varepsilon_0, ..., \varepsilon_J)$ chooses occupation j^* and labor supply ℓ^* that solve the following problem:

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

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 τ_g^j and κ_{ig}^{j}, along with reimbursement s.

2.2 Occupations

Production in each occupation $j = 0, ..., J$ 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, $j = 1, ..., J$, 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 $i = 2, ..., I$), with an elasticity of substitution σ_j. For each of these groups, there is an inner nest that aggregates labor bundles across the various types ($i = 1$ for the the native group and $i = 2, ..., I$ for the immigrant group) and all subtypes g with elasticity of substitution $\widetilde{\sigma}_j$. 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 σ_j: $y_j = A_j[{n^j_{\text{nat}}}^{\frac{\sigma_j-1}{\sigma_j}} + {n^j_{\text{imm}}}^{\frac{\sigma_j-1}{\sigma_j}}]^{\frac{\sigma_j}{\sigma_j-1}}$, where y_j is the output produced in occupation j, n^j_k is the labor bundle of group k in occupation j, and A_j is occupation-specific productivity. We index natives and immigrants with subscripts $k = \text{nat}$ and $k = \text{imm}$.[1]

The problem of the representative producer in market occupation $j = 1, ..., J$ 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:

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

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

[1] 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.

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

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

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 σ.

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 consists of prices and allocations such that (i) agents solve their problem taking prices as given; (ii) revenue collected through compensation wedges is equal to reimbursements; (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.[2] 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 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 $i = 1, ..., I$. We let $i = 1$ denote the set of natives and let $i = 2, ..., I$ 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.[3]

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.[4]

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 $i = 1, ..., I$ into G subtypes based on their level of education, age, and gender. Subtypes are indexed by $g = 1, ..., G$. 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 $i = 1, ..., I$ into 24 subtypes ($G = 24$)

[2] We pool all ten years together to increase the sample size and treat them as one cross section.

[3] Specifically, the group of immigrants includes naturalized citizens and non-citizens. However, we classify natives' foreign-born children as natives.

[4] We use the income level of immigrants' home countries for grouping, as it serves as a useful proxy for the quality of education, which often varies across origin countries.

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 and market occupations. We classify an individual as being in the non-market occupation if she is not employed or employed but usually works less than 10 hours per week. An employed individual who usually works more than 10 hours is assigned to one of the market occupations.

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.

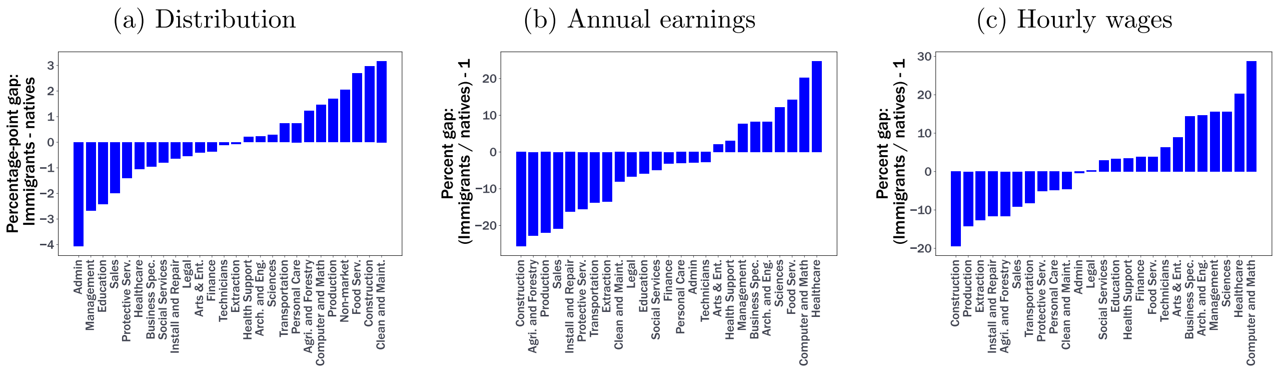
Annual earnings and hourly wages. We measure the annual earnings as total annual labor income (in 2019 dollars). We also measure hourly wages of individuals as the ratio of annual earnings to total annual hours worked. For each set of individuals of type i and subtype g in market occupation j, we compute 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

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. Panels (b) and (c) show the percent gap (calculated as immigrants/natives − 1) between their annual earnings and hourly wages.

relative to natives within each occupation. Thus, we next examine the extent to which outcomes 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 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 impact 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 those 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.[5] Our results reveal significant heterogeneity in earnings 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

[5]These are expressed relative to their 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	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
	Distribution						
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
	Annual earnings						
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
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
	Hourly wages						
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
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), $I_{\text{Low Eng}}$ denotes low English proficiency immigrants, $I_{\text{High Eng}}$ denotes high English proficiency immigrants, I_{LIC} denotes immigrants originating from low-income countries, and I_{HIC} denotes immigrants originating from high-income countries.

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.

These observations show that immigrants differ from natives in their occupations as well as in their earnings and wages. To what extent are these differences accounted for by differences in their productivities or by wedges? We investigate this in the following sections.

3.2 Estimation approach

We now present our approach to estimating model parameters. The parameter space is partitioned into two groups. The first is predetermined and set externally. The second is estimated to match 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 ξ, $\{\eta_i\}_{i=1}^{I}$, σ, $\{\sigma_j\}_{j=1}^{J}$, and $\{\widetilde{\sigma}_j\}_{j=1}^{J}$. We set the Frisch elasticity $\xi = 0.75$. As discussed in Section 2, the shape parameter η_i of the

Table 2: Estimation approach: Parameters and targets

Predetermined parameters

Parameter	Value	Description
ξ	0.75	Frisch elasticity
$\{\eta_i\}_{i=1}^{I}$	4	Frechet shape
σ	20	Elasticity across sectoral goods
$\{\sigma_j\}_{j=1}^{J}$	20	Elasticity across worker bundles between natives and immigrants
$\{\widetilde{\sigma}_j\}_{j=1}^{J}$	40	Elasticity across worker bundles between individual types and subtypes

Estimated parameters

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		

Target moments

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.

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. In our baseline calibration, we assume that the idiosyncratic productivity of natives and immigrants is drawn from a common Frechet distribution with shape η—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 et al. (2023), which we discuss using Figure A5 in Appendix C, we also recompute our main results in Section 7 when we instead assume that immigrants and natives are different in their underlying productivities.

We set $\sigma_j = \sigma \ \ \forall j = 1, ..., J$ 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).[6] 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 implied by our parameterization. Importantly, Appendix E also presents our main results when labor bundles between natives and immigrants are less substitutable $\sigma_j = 4.6 \ \ \forall j = 1, ..., J$ as in Burstein et al. (2020) or perfectly substitutable and shows that the aggregate gains from removing immigrant

[6] Their preferred estimate is 20 when the native-immigrant elasticity is the same for all education groups.

wedges are amplified when we lower σ_j. Further, we approximate perfect substitution in the inner nest across labor bundles within natives and immigrants by setting $\widetilde{\sigma}_j = 40 \ \ \forall j = 1, ..., J$.

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 $b \in \{1, ..., I\}$ and $m \in \{1, ..., G\}$, respectively. Our first normalization consists of setting $z^0_{bm} = 1$. 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: $\tau^0_g = 0$ and $\kappa^0_{ig} = 0 \ \forall i, g$. We also assume that natives that belong to base type and subtype (b, m) face no compensation wedges in any of the market occupations: $\tau^j_m = 0 \ \forall j$. Third, we normalize the preference for the non-market occupation such that $\nu^0_g = 1 \ \forall g$. Fourth, we set immigrant labor supply wedges to zero in the non-market occupation: $\gamma^0_{ig} = 0 \ \forall i, g$. 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: $\gamma^j_{1g} = 0 \ \forall g, j$ and $\kappa^j_{1g} = 0 \ \forall g, j$.

We use the remaining parameters to target the share of individuals (i, g) in $j \ \forall i, g, j$, the average annual earnings of individuals (i, g) in j relative to the average annual earnings of the base (type, subtype) (b, m) in $j = 1$, and the average hourly wages of individuals (i, g) in j relative to the average hourly wages of the base (type, subtype) (b, m) in $j = 1$.[7] 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: $\widetilde{\sigma}_j = \infty \ \forall j = 1, ..., J$. Appendix C provides derivations of the equations used in this section.

The key challenge is to separately identify immigrant labor supply wedges γ^j_{ig}, immigrant compensation wedges κ^j_{ig}, and productivity z^j_{ig}, which all vary by occupation and worker type. Our identification approach builds on Hsieh et al. (2019) and exploits the structure of the Roy model with Fréchet-distributed idiosyncratic productivities, which delivers closed-form expressions linking occupational sorting and earnings to these parameters. We begin by identifying

[7] As shown in Table 2, we have more moments for annual earnings than hourly wages since 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 λ of weighted average of 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 λ of the weighted average of 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. Appendix E provides our main results under alternative values of λ.

labor supply wedges γ_{ig}^{j} using the ratio of average earnings across occupations for immigrants versus natives of the same type and subtype (Equation 2 below). As emphasized by Hsieh et al. (2019), this earnings ratio reflects only differences in utility—captured by preferences and labor supply wedges—because individuals with higher idiosyncratic productivity draws sort into less desirable occupations, keeping average earnings invariant to productivity and compensation wedges. Given these wedges, we next recover productivity z_{ig}^{j} using differences in earnings-to-wage ratios and occupational shares across occupations (Equation 4); higher productivity leads individuals to sort more intensively into certain occupations and supply more labor conditional on working. Finally, we identify immigrant compensation wedges κ_{ig}^{j} from wage gaps between immigrants and natives within the same occupation, controlling for productivity and supply-side effects via the model's CES labor aggregation (Equation 5). This structure ensures that each parameter is separately identified from distinct and economically interpretable variation in data.

Using this strategy, the full set of parameters is identified using information on how individuals are allocated across occupations, their average annual earnings, and their hourly wages. This enables us to estimate the model with rich heterogeneity across individuals and jobs, while tightly linking theoretical objects to observable variation in the data.

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

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

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

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

where Earnings_{ig}^{j} is the geometric average annual earnings across all individuals of (i, g) in occupation j. In the model, the earnings are given by the right-hand side of the 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 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.[8] That is, the earnings of natives of

[8]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 λ of the weighted average of annual earnings across all market occupations. This

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:

$$1 + \gamma_{ig}^j = \lambda \left(\nu_g^j \frac{\text{Earnings}_{ig}^j}{\text{Avg. market earnings}_{ig}} \right)^{-1} = \left[\left(\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{1g}^j} \right) \Big/ \left(\frac{\text{Avg. market earnings}_{ig}}{\text{Avg. market earnings}_{1g}} \right) \right]^{-1}. \quad (2)$$

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 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:

$$z_{ig}^0 = \left(\frac{\text{Avg. market earnings}_{ig}}{\text{Avg. market earnings}_{bm}} \right)^{\frac{1}{1+\xi}} \left(\frac{\text{Fraction of non-employed}_{ig}}{\text{Fraction of non-employed}_{bm}} \right)^{\frac{1}{\eta}}, \quad (3)$$

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

implies that $\text{Earnings}_{ig}^0 = \lambda \times \text{Avg. market earnings}_{ig} \ \forall i, g$.

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:

$$\frac{z^j_{ig}}{z^0_{ig}} = \frac{\text{Earnings}^j_{ig}/\text{Wages}^j_{ig}}{\text{Earnings}^0_{ig}/\text{Wages}^0_{ig}} \times \left(\frac{\text{Fraction of employed}^j_{ig}}{\text{Fraction of employed}^0_{ig}}\right)^{\frac{1}{\eta}}, \tag{4}$$

where Fraction of employed$^j_{ig}$ denotes the fraction of individuals of type (i, g) in occupation j, and Wages$^j_{ig}$ 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 $(1-\tau^j_{ig}-\kappa^j_{ig})w^j_{ig}$. 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^j_{ig} $\forall i, g$ across market occupations. Equation (4) 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 j is higher or if a higher fraction of individuals chooses j than the non-market occupation.

Before proceeding to our discussion on the identification of compensation wedges, we comment on our mapping of hourly wages in the data with hourly wages in the model by measuring them as $(1 - \tau^j_{ig} - \kappa^j_{ig})w^j_{ig}$. This assumption is made in order to estimate z_{ig} for each occupation j, as we discuss more below. In particular, we assume that the annual hours worked of an individual (i, g) in occupation j in the model is given by $\ell z^j_{ig}\varepsilon_j$, creating variation in labor supply even among those who choose the same l. As such, our interpretation of $z^j_{ig}\varepsilon_j$ is that it captures the ability to supply more hours or the ability to supply the same amount of hours at a lower disutility cost, and not the ability to produce more per hour.

To understand how this assumption affects our conclusions, in Section 7, we consider two modifications to our baseline analysis. First, we measure hourly wages in the model as $w^j_{ig}z^j_{ig}\varepsilon_j$ instead of $(1 - \tau^j_{ig} - \kappa^j_{ig})w^j_{ig}$. This case corresponds to the interpretation that $z^j_{ig}\varepsilon_j$ captures the ability to produce more per hour. Importantly, in this case, we are still able to derive similar analytical expressions to back out the productivity and wedge parameters as in our baseline analysis.[9] Table 10 provides our main results under this mapping. It shows that while productivity gains from removing immigrant wedges in this case are similar to those under the baseline assumption, gains in hours and employment become smaller. Second, we consider an alternative model where the labor supply is inelastic. In this case, we do not need to target

[9] As such, it is critical for our derivations that wedges $(1 - \tau^j_{ig} - \kappa^j_{ig})$ and productivity terms $z^j_{ig}\varepsilon_j$ are not multiplicative when we map hourly wages in our model. If they do, we cannot estimate z^j_{ig} across occupations but can only estimate productivities independent of occupations, i.e., z_{ig}.

hourly wages, and thus do not need to make assumptions on how to define hourly wages in the model. Then, we can only estimate productivities independent of occupations, i.e., z_{ig}. Table 10 shows that the gains from removing immigrant wedges are significant but smaller in this case.

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 τ 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.

Next, we 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 model implies:

$$\frac{1 - \tau_g^j - \kappa_{ig}^j}{1 - \tau_g^j} = \frac{\text{Wages}_{ig}^j}{\text{Wages}_{1g}^j} \left\{ \frac{\sum_{q \in \mathcal{I}_i} \sum_{r=1}^{G} N_{qr} \left(z_{qr}^j\right)^{1+\xi} \left[(1 + \gamma_{qr}^j)\nu_r^j \text{Wages}_{qr}^j\right]^{\xi} \left(p_{qr}^j\right)^{\frac{\eta-(1+\xi)}{\eta}}}{\sum_{r=1}^{G} N_{1r} \left(z_{1r}^j\right)^{1+\xi} \left[(1 + \gamma_{1r}^j)\nu_r^j \text{Wages}_{1r}^j\right]^{\xi} \left(p_{1r}^j\right)^{\frac{\eta-(1+\xi)}{\eta}}} \right\}^{\frac{1}{\sigma_j}}, \quad (5)$$

where $\mathcal{I}_i$ is the set of immigrant types. Then, using data on wages and allocations across (type, subtype) pairs, 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 κ in this occupation would be positive. For κ to be zero, immigrants would need to be paid relatively more than natives given their relative scarcity.[10]

[10] Immigrants from certain countries of origin may benefit from larger or more established communities, potentially allowing them to face lower labor market barriers. While we cannot identify such network effects in our data, our approach already implicitly captures these effects. In particular, Equation (5) implies that, conditional on other observables such as wages, hours worked, and masses of worker groups across occupations, if we observe

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:

$$A_j = \left\{ \left(\frac{\text{Wages}^j_{bm}}{\text{Wages}^1_{bm}} \right)^{\sigma} \frac{\sum_{g=1}^{G} N_{bg} \left(z^j_{bg}\right)^{1+\xi} \left[\nu^j_g \text{Wages}^j_{bg}\right]^{\xi} \left(p^j_{bg}\right)^{\frac{\eta-1}{\eta}}}{\sum_{g=1}^{G} N_{bg} \left(z^1_{bg}\right)^{1+\xi} \left[\nu^1_g \text{Wages}^1_{bg}\right]^{\xi} \left(p^1_{bg}\right)^{\frac{\eta-1}{\eta}}} \right\}^{\frac{1}{\sigma-1}}. \tag{6}$$

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 (6) allows us to obtain 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.

3.4 Properties of the efficient allocation

Before we proceed to estimate the immigrant wedges and to study their macroeconomic effects, we first investigate the equilibrium of our model in the absence of distortions. These efficient allocations serve as the benchmark relative to which all distortions are estimated.

To simplify our discussion, we start by focusing on the case where natives and immigrants are perfect substitutes, i.e., $\sigma_j = \infty\, \forall j$. Then, we define the efficient equilibrium allocations to be given by the equilibrium when there are no immigrant-specific barriers, i.e., $\gamma^j_{ig} = 0$ and $\kappa^j_{ig} = 0$ $\forall i, g, j$. Thus, in this case, natives and all immigrant types are subject to the same level of distortions across occupations. We characterize two properties of the efficient allocation.

First, Equation (5) implies that natives and immigrants of any given immigrant type i with same subtype (i.e., observable characteristics) g should earn the same average hourly wages in all occupations j. Second, Equation (2) implies that the ratio of average annual earnings for natives and immigrant type i with the same subtype g and occupation j is equal to their ratio of average market earnings, and thus is independent of occupation j. These two properties of the efficient allocation then suggest that the ratio of average annual hours worked for natives and immigrant type i with the same subtype g is the same for all occupations j.

Are these properties of the efficient allocation in line with the data? Empirical results presented in Figure 1 and Table 1 suggest that (i) immigrant-native average hourly wage gaps are nonzero across all occupations and magnitude of these gaps largely differ across occupations and (ii) immigrant-native average annual earnings gaps are not the same across occupations.[11] Thus,

a higher fraction of employment of certain (type, subtype) (i, g) in an occupation j relative to natives, then immigrant compensation wedges κ should be smaller for this immigrant group (i, g) in that occupation j.

[11] To be clear, results in Figure 1 do not condition on a specific immigrant type i and subtype g, and results in Table 1 only condition on immigrant type but do not condition on subtype g. However, even when we focus on specific immigrant type i and compare outcomes in the data between immigrant type i and natives with the same subtype g, these properties of the efficient allocation are rejected by the data.

our empirical findings reject the predictions of the efficient allocation.

We now comment on two potentially important assumptions that are relevant for this comparison between the data and the efficient allocation. First, for this comparison, we focus on a case where natives and immigrants are perfect substitutes, i.e., $\sigma_j = \infty \, \forall j$ instead of $\sigma_j = 20 \, \forall j$. Our baseline choice of $\sigma_j = 20$ is motivated by empirical studies on the degree of substitutability between immigrant and native labor supply. Even without perfect substitution, we are able to derive key equations analytically (see Section 3.3), allowing us to study the more general case while still providing insights on the identification of model parameters using these equations. However, $\sigma_j = 20$ already implies a high degree of substitutability, close to the perfect substitution case assumed in this section when exploring the properties of the efficient allocation. For these reasons, the small discrepancy between our calibrated economy—which is used to estimate wedges in the next section—and the efficient allocation benchmark is second order.

Second, our model assumes that idiosyncratic productivities across occupations are drawn from a Frechet distribution and *i.i.d.* across individuals and occupations. We borrow this assumption from McFadden (1972), Eaton and Kortum (2002), and Hsieh et al. (2019), the latter implementing it in a similar context to ours when estimating labor market barriers across race and gender in the U.S. This assumption is important to ensure the tractability of the solution while also allowing us to analytically characterize the identification approach and efficient allocation. Further, it determines the link between allocations, earnings, and wages. For instance, the efficient allocation implies that recent immigrants from India who are fluent in English and more productive in computer occupations than natives (conditional on gender, education, and age) should earn the same average hourly wages as natives. This is because, under the assumption of *i.i.d.* Frechet draws, these immigrants would have a higher employment share in these occupations but they would have the same average wages in equilibrium conditional on that employment share. However, our empirical findings (Figure 1 and Table 1) show that actual outcomes diverge significantly from this efficient benchmark. This suggests that the large and varying earnings gaps between natives and immigrants across occupations cannot be easily explained by alternative distributions for idiosyncratic productivity draws. For example, as Table 1 shows, relative to recent immigrants, the average annual earnings of natives is 59% (1.08/0.68) larger in routine manual occupations and 2% (1.78/1.82) lower in non-routine cognitive occupations.[12]

4 Immigrant Wedges: Estimates and Impact

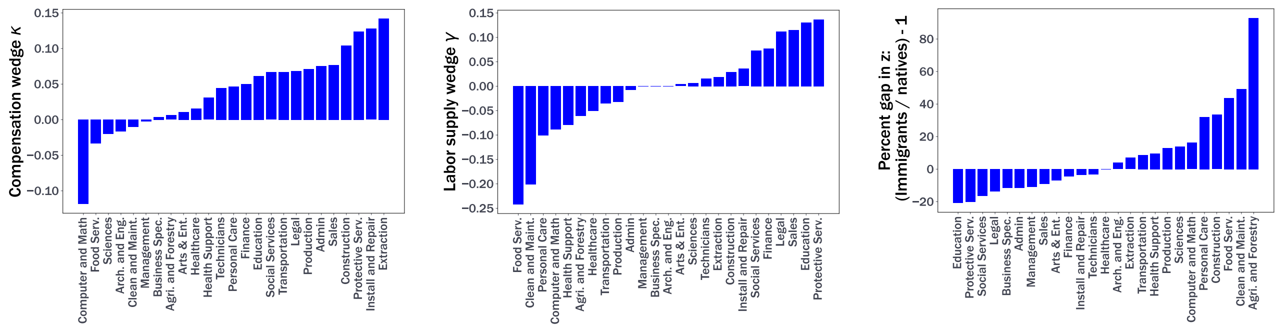
In this section, we study the extent and implications of immigrant wedges in the U.S. Section 4.1 estimates the parameters of the model following the approach described in the previous section.[13]

[12]Again, these conclusions remain largely unchanged when we also condition on observable characteristics and compare outcomes within a specific occupation among the list of two-digit occupations we analyze.

[13]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 $\widetilde{\sigma}_j = 40 \, \forall j = 1, ..., J$

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

(a) Immigrant compensation wedge (b) Immigrant labor supply wedge (c) Relative productivity



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

Section 4.2 provides evidence to validate our interpretation of the model-implied wedges as meaningful barriers faced by immigrants. Sections 4.3 and 4.4 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 (κ and γ) 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 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

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 $\widetilde{\sigma}_j$ to approximate perfect substitution.

Table 3: Estimation results

Occupation type	Immigrant compensation wedge κ N	I_{0-10}	I_{10+}	$I_{Low\ Eng}$	$I_{High\ Eng}$	I_{LIC}	I_{HIC}	Common comp. wedge τ
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
	Immigrant labor supply wedge γ							**Common**
Occupation type	N	I_{0-10}	I_{10+}	$I_{Low\ Eng}$	$I_{High\ Eng}$	I_{LIC}	I_{HIC}	pref. ν_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
	Worker productivity z							**Occupation**
Occupation type	N	I_{0-10}	I_{10+}	$I_{Low\ Eng}$	$I_{High\ Eng}$	I_{LIC}	I_{HIC}	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 τ, immigrant compensation wedges κ, common preference shifter ν, immigrant labor supply wedges γ, 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.

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 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 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 κ^j_{ig} and labor supply wedges γ^j_{ig}, and productivities z^j_{ig}. While we focus on immigrant wedges and productivities, we also report common compensation wedges τ^j_g and preference shifters ν^j_g, and occupation productivities A_j.

We find large differences in immigrant barriers and productivities by time since immigration. Recent immigrants face larger compensation wedges across all occupations compared with established 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 differences in immigrant barriers and productivity based on English proficiency. Immigrants with lower English skills have higher compensation wedges in all occupations. They also have negative labor supply wedges, with the magnitude of these wedges largely varying 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 Immigrant wedges: Validation exercises

A potential concern about the interpretation of our estimated wedges is that they might reflect productivity differences rather than true immigrant barriers. We now provide additional evidence to validate our interpretation of the wedges as meaningful barriers faced by immigrants.

Immigrant wedges by time since immigration. We first examine how our estimated wedges evolve as immigrants spend more time in the host country. If our estimated wedges reflect genuine barriers rather than permanent differences in productivity, we would expect them to decrease as immigrants assimilate into the labor market. To test this prediction, we reemphasize our findings from the second and third columns of Table 3, where we show that immigrant compensation wedges and labor supply wedges are systematically larger for recent immigrants

Table 4: 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.

(those in the U.S. for less than 10 years) than for established immigrants (those in the U.S. for more than 10 years). This pattern aligns with previous research (e.g., Dostie, Li, Card, and Parent 2020), indicating a period of adjustment and integration for new immigrants.

In particular, we find that immigrant compensation wedges are significantly larger among recent immigrants across all occupation groups. For example, in routine manual occupations, recent immigrants have an average compensation wedge of 0.12, compared to 0.07 for established immigrants. Similarly, immigrant labor supply wedges also display notable differences. For instance, recent immigrants face a substantially larger labor supply wedges in routine cognitive occupations (0.10 versus 0.03). These systematic reductions in the magnitudes of immigrant wedges over time support the interpretation of wedges as genuine labor market barriers faced by immigrants, rather than persistent productivity gaps between natives and immigrants.

Immigrant wedges: Model vs external evidence. While the above discussion establishes the reasonableness of our estimated immigrant wedges within our model, it is necessary to validate these wedges against potential immigrant barriers that we can measure in the data. For this reason, we now compare the model-implied wedges across occupations with a prominent barrier faced by newcomers: country-specific occupational 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.[14] As expected, we find that the fraction of jobs requiring a license is highest in healthcare, legal, education, healthcare support, and protective services occupations, while it is lowest in cleaning and maintenance, admin, and agriculture occupations. We compare this measure of licensing intensity with immigrant compensation wedges and immigrant labor supply wedges implied by our model.

Table 4 reports correlations between model-implied immigrant wedges and the fraction of

[14] Using the CPS, we also apply the same sample selection and definition of being employed as in Section 3.1.

jobs requiring a license across occupations in the U.S. For all immigrants, we find that the correlations are positive, indicating that model-implied immigrant wedges are larger in occupations where license requirements are more prevalent. We also find that these correlations are higher when we compare licensing requirements with immigrant wedges for recent immigrants, but the correlations 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. Importantly, this result also serves as another external validation of our estimates of immigrant wedges. This is because, if our estimates of wedges were capturing not only labor market barriers faced by immigrants but also unobserved productivity differences between natives and immigrants, we would expect correlations between model-implied wedges and licensing requirements to remain high as time since arrival increases. However, the reduction of these correlations over time suggests that model-implied wedges capture genuine labor market barriers to entry in occupations.

In Section 6, we further extend this validation exercise by leveraging external cross-country data to compare the model-implied immigrant wedges across countries with international survey measures of immigrant integration and host-country attitudes toward immigrants.

Alternative modeling assumptions. In addition to the results provided above, we also perform robustness checks on our modeling assumptions related to immigrant productivity differences in the model. In Section 7, we relax our baseline assumption of identical underlying productivity distributions for immigrants and natives and explore alternative mappings between productivity differences and observable outcomes in the data.

4.3 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 reduced to the levels of natives; i.e., $\gamma_{ig}^{j} = 0$ and $\kappa_{ig}^{j} = 0\ \forall i, g, j$. Thus, in the latter, immigrants still face barriers, but they are subject to the same level of distortions across occupations as natives.

Aggregate real GDP gains. The first column in Table 5 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%. When we only remove immigrant compensation wedges but keep immigrant labor supply wedges unchanged, real GDP increases by 5.9%, implying that most of the gains are due to the removal of compensation wedges. Importantly, these gains from removing wedges should be taken as an upper bound because this exercise eliminates all immigrant-specific wedges, which may not be feasible

Table 5: Aggregate and sectoral effects of removing wedges

	Percent change				Change in
Occupation type	Real GDP	TFP	Employment	Hours	immigrant share (pp)
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

Notes: This table 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.

in terms of the implementation, and it ignores potential costs involved in removing these wedges.

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.[15] Table A3 implies 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 (6.98/28.2). Hence, existing barriers undermine the contribution of immigrants and removing them largely 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 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.[16]

Real GDP gains across occupations. Underlying the aggregate gains, the removal of immigrant wedges have heterogeneous effects across occupations.[17] 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.

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

[15]We implement the economy without immigrants by setting the mass of immigrants to be infinitesimally small.

[16]Table A4 shows 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.

[17]While Table 5 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.

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, Table A4 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 occupation groups, but with a varying magnitude. Gains in hours worked contribute the most to GDP gains in routine manual occupations, while these gains are the least important in accounting for gains in non-routine cognitive occupations.[18]

4.4 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 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

[18]Table A5 presents the distribution of reallocation patterns for immigrant type/subtypes. Overall, it shows that removing immigrant wedges allows disadvantaged immigrant groups to either reallocate from the non-market occupation to market occupations or to switch across market occupations.

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

Category	Immigrant type/subtype	Real GDP (% change)	Share of population (baseline level, %)	Real GDP growth 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.

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 A6. 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.[19]

[19] We also investigate heterogeneity in the gains from removing immigrant wedges across occupations. As shown in Table A7, we find that real GDP gains per immigrant are highest when immigrant barriers are removed in

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?

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 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 keep this section focused, 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) measure elasticities of labor market outcomes of various groups to this shock by comparing outcomes in Miami and control cities before and after the arrival of the Marielitos to Miami (the "Marielitos shock"). Appendix D provides a detailed discussion on these empirical elasticies.

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 for two reasons. First, computing these elasticities in the model allows us to document how an increase in immigration affects

non-routine cognitive occupations and lowest when they are removed in non-routine manual occupations.

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.

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 economy. Appendix D provides details of this exercise. We then solve the model under the Marielitos shock and compute changes in outcomes in this model relative to the baseline. 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. The empirical estimates show that the inflow of Mariel immigrants had limited effects on the outcomes of natives but relatively larger effects on the wages of immigrants in Miami.[20] 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

[20] We note that empirical estimates vary depending on the specification or time horizon given the small number of observations in the data. However, in these scenarios, the estimated effects of this shock on labor market outcomes are smaller for natives and relatively larger for immigrants, as in our model.

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

Given that the model is static, we consider two separate counterfactuals. In the first, we start from the baseline economy and introduce 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. In the second, we start from an economy without immigrant wedges and introduce the same 10% increase in immigrants. The only difference between the two scenarios is the presence or absence of immigrant wedges in the initial economy before the immigration shock. 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 when considering a pool of new immigrants whose distribution across types and subtypes is identical to the distribution of recent immigrants in the U.S. We find that this policy change increases productivity by 0.04%. Thus, new immigrants not only mechanically increase output, but also increase the aggregate productivity.

Row 2 up to the last show the effects of increasing immigration when the pool of new immigrants is restricted to a particular immigrant type or subtype.[21] 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 amplifies the productivity gains from immigration. Importantly, we also find that the ranking of productivity gains from

[21] 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.

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).

admitting a particular type of immigrant changes if immigrant wedges are removed. For instance, 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 groups only if they also face no barriers.

6 Immigrant Wedges Across Countries

The previous sections revealed that the immigrant barriers in the U.S. have sizable aggregate, distributional, and policy implications. This result motivates a deeper understanding of the underlying drivers of immigrant wedges and the gains from their removal. We now 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 cross-country microdata, we compute the magnitudes of immigrant wedges across countries and their macroeconomic implications. Second, we use cross-country differences in immigrant outcomes to provide further insights on underlying labor market features that determine the gains from removing 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.[22]

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.[23] 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).[24] 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.

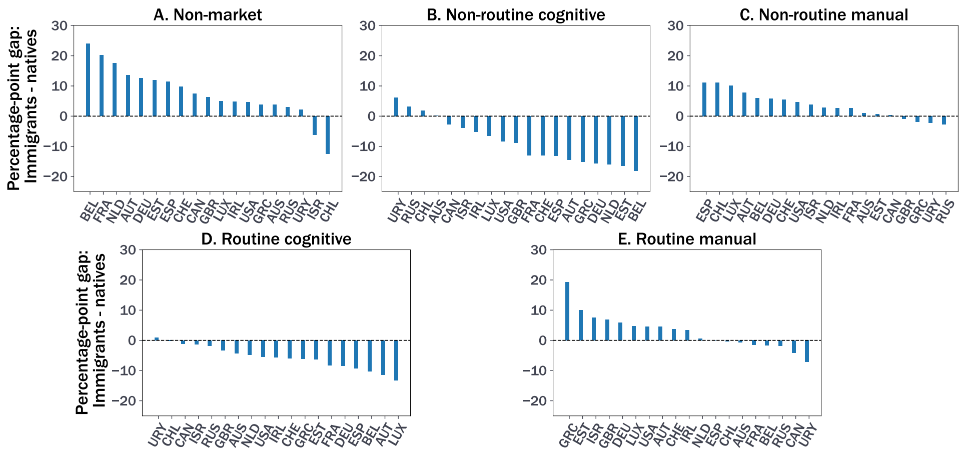
Labor market outcomes of immigrants across countries. We start by documenting salient differences in labor market outcomes between immigrants and natives across countries. We focus on the distribution of immigrants and natives across occupations as well as their av-

[22] 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 years to increase the sample size.

[23] 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.

[24] In addition, some individuals are classified to be in the non-market occupation, as in Section 3.1.

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



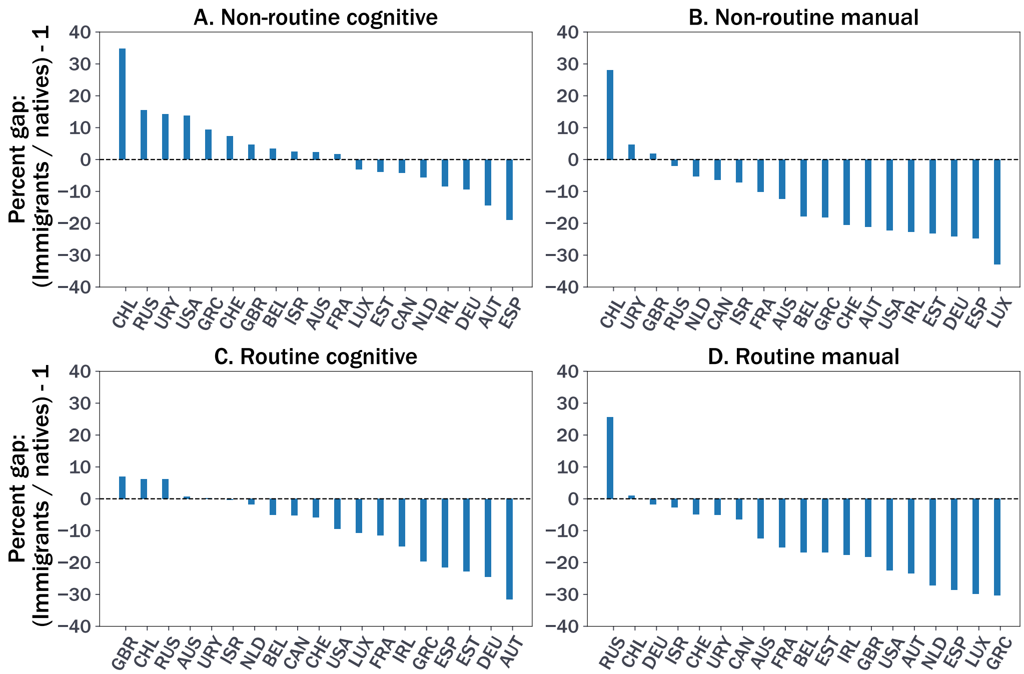
Notes: This figure presents differences in allocations between immigrants and natives across countries using data from the LIS. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) and show the percentage-point gap (immigrants − natives) between fractions of immigrants and natives in each occupation across countries.

erage 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 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 largely varies across countries. For example, while this gap is around 5 percantage 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) and overrepresented in non-routine manual occupations (the occupation with the lowest average earnings) 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

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.

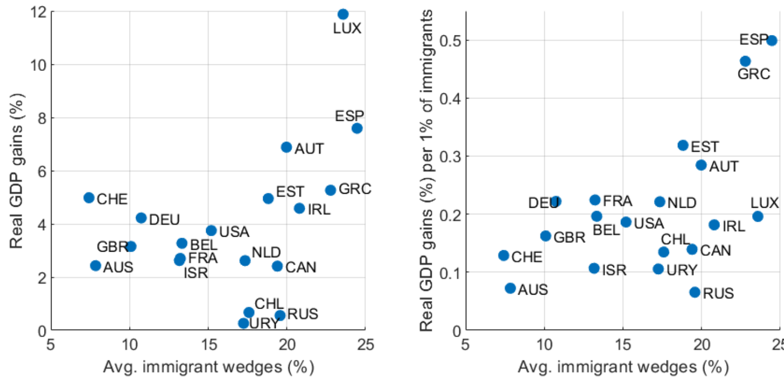
and occupations. Interestingly, we find that, in 11 of 19 countries in our sample, the average earnings of immigrants are larger than those of natives in non-routine cognitive occupations, exhibiting significant dispersion across countries. For example, in these occupations, the average earnings of immigrants 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.[25]

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

[25]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 GDP gains from removing immigrant wedges across countries. The left panel presents 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.

differences in immigrant wedges across countries or are accounted for by cross-country differences 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.

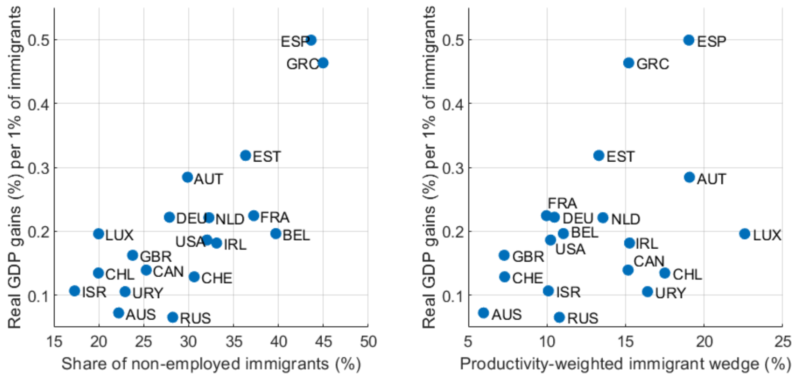
The left panel of Figure 5 presents the relation between the average of immigrant compensation wedges across countries (x-axis) and real GDP gains from removing immigrant wedges (y-axis).[26] We find that there is a large degree of dispersion in immigrant barriers (from 7.42% in Switzerland (CHE) to 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)).[27] 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

[26]We focus on immigrant compensation wedges, as they account for most of the output gains.

[27]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 7.

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



Notes: This figure shows the sources behind the differences in GDP gains from removing immigrant wedges across countries. The left panel presents the share of non-employed immigrants against the GDP gains per immigrant. The right panel plots the average productivity-weighted immigrant compensation wedges 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. Moreoever, 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.

Cross-country immigrant wedges: Model vs. external evidence. Recall in Section 4.2 that we use external data to validate model-implied wedges for the U.S. with external evidence. We now use a new dimension of cross-country data to perform a similar validation exercise by comparing immigrant wedges across countries with external measures of immigrant 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. 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 survey data from the Gallup World Poll, which asks individuals across countries about their attitudes toward immigrants.[28] The second index is the Migrant Integration Policy Index (MIPEX) collected by Solano and Huddleston (2020), which compares immigrant policies across countries.[29] Higher values of these indexes indicate attitudes or policies that are more friendly toward immigrants.

To contrast the model-implied measures of wedges with these external estimates, we compute the correlation between them for the countries in our LIS sample.

[28] 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.

[29] These include measures on how easy for immigrants to gain permanent residence and citizenship in the host country, whether immigrants have equal rights 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.

Table 9: 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.

Table 9 shows 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.

7 Discussion of Results

Finally, we examine the role played by model specifications 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 10.

Modeling heterogeneity across occupations and workers. We examine the importance of accounting for 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. 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 in this case. This is because 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 instead of the 456 groups in the baseline. Table 10 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.

Overall, we conclude that accounting for rich heterogeneity in occupations and worker groups is important for the aggregate gains from removing immigrant wedges.

An alternative mapping of hourly wages in the model. In Section 3.3, we map hourly wages in the data with hourly wages in the model by measuring them as $(1 - \tau_{ig}^j - \kappa_{ig}^j)w_{ig}^j$. This assumption implies that annual hours worked in the model is $\ell z_{ig}^j \varepsilon_j$ and that $z_{ig}^j \varepsilon_j$ captures the ability to supply more hours or the ability to supply the same amount of hours at a lower

Table 10: Gains from removing immigrant wedges under alternative specifications

	Percent change				Change in
	Real GDP	TFP	Employment	Hours	immigrant share (pp)
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
Alternative mapping of hourly wages	3.60	2.26	0.56	0.75	0.50
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 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; alternative mapping of hourly wages refers to a case where we measure hourly wages in the model as $w^j_{ig} z^j_{ig} \varepsilon_j$ instead of $(1 - \tau^j_{ig} - \kappa^j_{ig}) w^j_{ig}$; inelastic labor supply refers to a model where we shut down the endogenous labor supply; and higher productivity draws for immigrants refers to a model where 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.

disutility cost, and not the ability to produce more per hour. To understand whether this assumption is important, we consider an alternative mapping of hourly wages in the model such that hourly wages are given by $w^j_{ig} z^j_{ig} \varepsilon_j$. This case corresponds to the interpretation that $z^j_{ig} \varepsilon_j$ captures the ability to produce more per hour. Table 10 shows that while productivity gains from removing wedges in this case are similar to those under the baseline assumption, gains in hours and employment become smaller. This is because, when we measure hourly wages as $w^j_{ig} z^j_{ig} \varepsilon_j$, removing wedges does not affect wages, leading to smaller changes in labor supply. However, as Table 10 reveals, productivity gains from removing wedges remain similar and significant.

Modeling endogenous labor supply. Next, we examine the role of elastic labor supply by considering a version of the model that abstracts from this channel. This exercise is also useful as it eliminates the need to differentiate between hourly wages and annual earnings in the model and tests how our assumption in Section 3.3 that the hourly wages in the model are $(1 - \tau^j_{ig} - \kappa^j_{ig}) w^j_{ig}$ affects our main results.[30] Table 10 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.

Heterogeneous productivity distributions between natives and immigrants. We assumed that idiosyncratic productivities of natives and immigrants across occupations are drawn from a common Frechet distribution, motivated by findings in Martellini et al. (2023). We now provide our results when we instead assume that productivities are drawn from different distributions. Specifically, we assume that the shape parameter of the Frechet distribution is different

[30] In this case, however, we can only estimate productivities independent of occupations, i.e., z_{ig}.

for immigrants such that the mean of productivity draws is 10% higher for immigrants. The reason why we focus on this case is that the estimation strategy of human capital gaps between natives and immigrants in Martellini et al. (2023) does not account for immigrant wedges when comparing wages between natives and immigrants. Absent wedges, their findings suggest a specification where productivities of natives and immigrants across occupations are drawn from a common distribution. Thus, accounting for wedges motivates this alternative specification.

A higher mean of the 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 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 A8 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.

8 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. The gains from removing immigrant barriers in the U.S. are around 7% of GDP. These gains arise from both increased employment and 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. 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, 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, immigrant wedges affect the impact of immigration policies. Thus, our results suggest that policymakers should jointly address immigrant entry and 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.

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

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

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 $j = 1, ..., J$.

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 $j = 1, ..., J$.

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:

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

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

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

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 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.[1] In addition

[1]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

Non-routine cognitive	Non-routine manual
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)	***Routine manual***
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)
Routine cognitive	
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.[2]

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.

Given that we pool observations between 2010 and 2019 in our data, it is not common to have small cell sizes. However, when a cell has no observations, we assign an infinitesimally small mass of individuals, as well as infinitesimally small values for hourly wages and annual earnings, to that cell. Whenever a cell has at least one observation, we use information for these cells. Since what matters is the population share of these cells, which is small given the large number of cells, these cases do not significantly affect our results. We have experimented with different cutoff values higher than one observation and found similar results.

[2]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).

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 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.

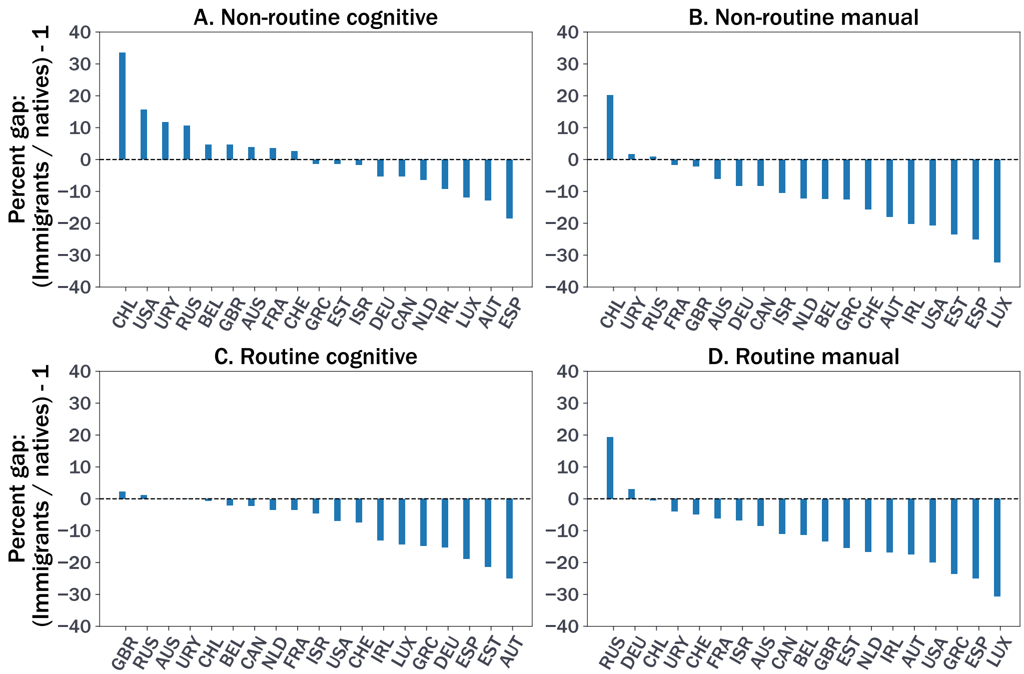
The LIS database provides individual-level data on demographics, including immigration status, and labor market outcomes. Similar to the ACS, we define immigrants to be foreign-born individuals. In terms of labor market related variables, the LIS contains individual-level data on employment status (employed 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.[3]

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.[4] 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

[3] 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.

[4] For France, occupation codes are based on two-digit European Socieconomic Groups (ESeG) classification, where we use a crosswalk to obtain two-digit ISCO codes from ESeG codes.

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



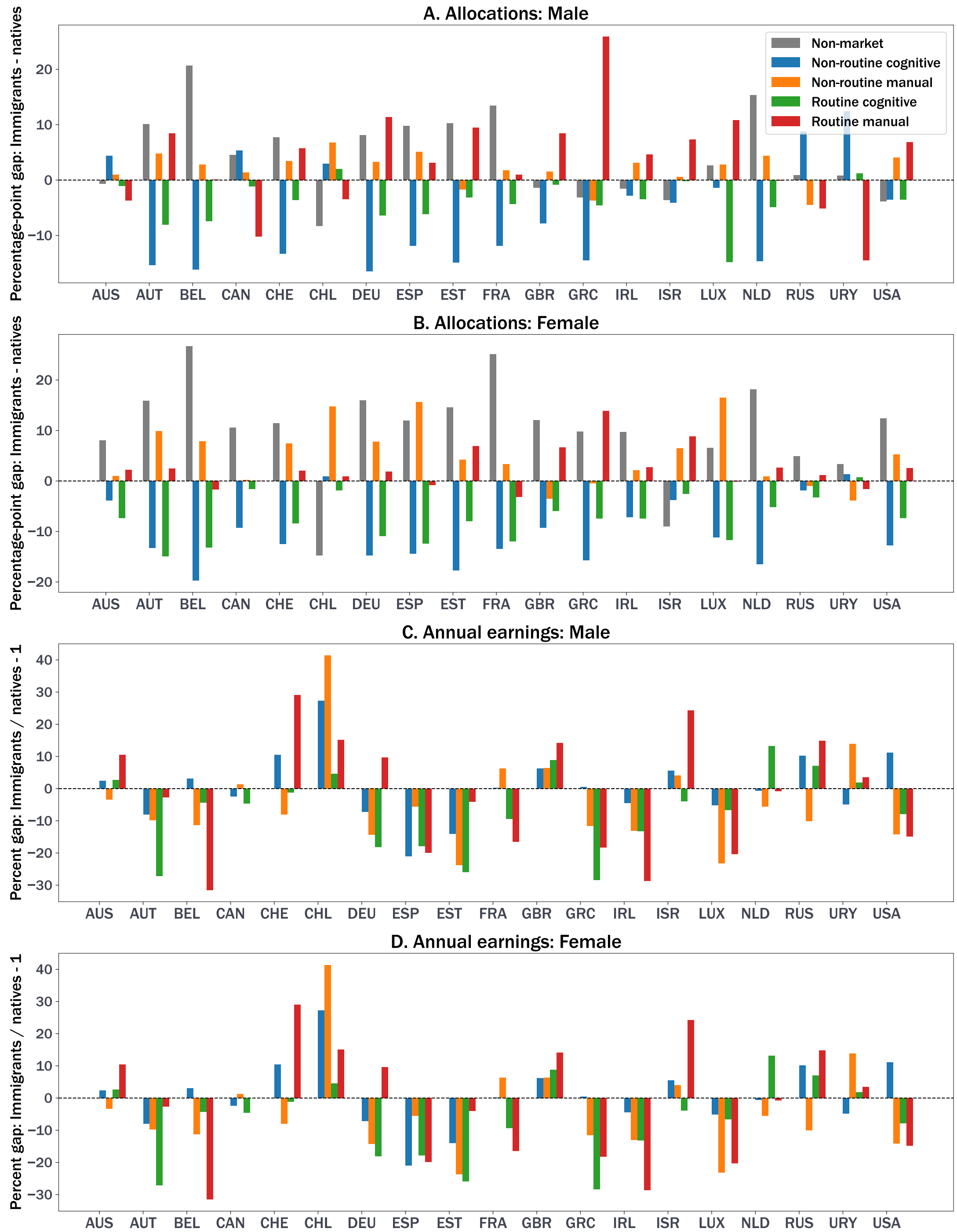
Notes: The figure shows the percent gap (calculated as immigrants/natives − 1) between hourly wages of immigrants and natives in each occupation across countries using data from the LIS.

and related workers, plant and machine operators and assemblers, and elementary occupations to routine manual occupations.[5] 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 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.

[5] These choices are broadly consistent with the one-digit occupation classifications using the SOC codes.

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

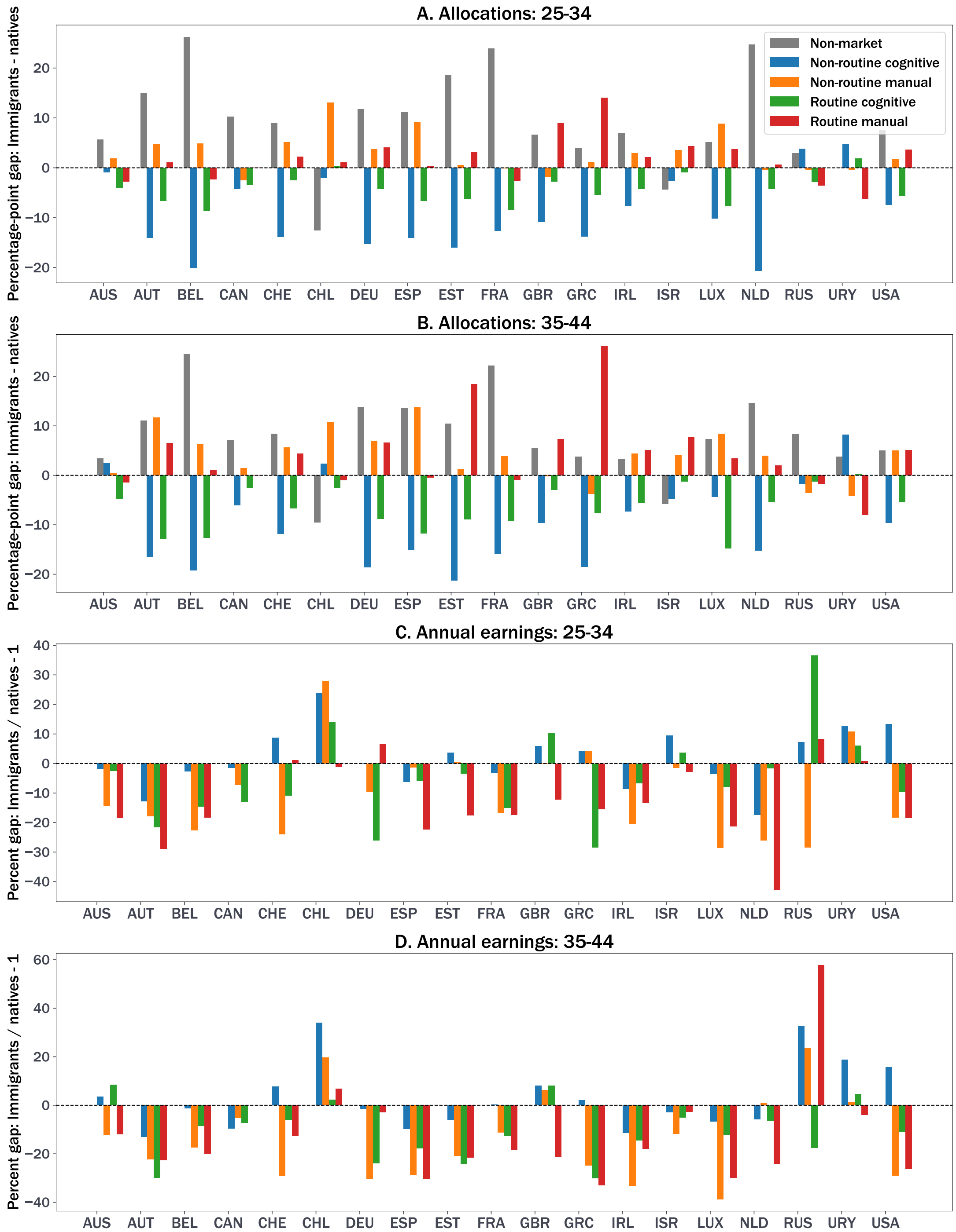


Notes: This figure presents differences by gender in labor market allocations and annual earnings between immigrants and natives across countries. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average annual earnings 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.[6] 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)-(6) 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 $j = 0, ..., J$ is given by:

$$\text{Fraction of employed}_{ig}^{j} = \frac{\left[(1+\gamma_{ig}^{j})\nu_{g}^{j}\left(1-\tau_{g}^{j}-\kappa_{ig}^{j}\right)w_{ig}^{j}z_{ig}^{j}\right]^{\eta}}{\sum_{q=0}^{J}\left[(1+\gamma_{ig}^{q})\nu_{g}^{q}\left(1-\tau_{g}^{q}-\kappa_{ig}^{q}\right)w_{ig}^{q}z_{ig}^{q}\right]^{\eta}}.$$

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

[6] Results for hourly wage gaps are similar to those for annual earnings gaps.

$$
\begin{aligned}
\text{Earnings}_{ig}^{j} = \; & \left[(1/p)\left(1+\gamma_{ig}^{j}\right)\nu_{g}^{j}\right]^{\xi}\left[\left(1-\tau_{g}^{j}-\kappa_{ig}^{j}\right)w_{ig}^{j}z_{ig}^{j}(1+s)\right]^{1+\xi} \\
& \times\left(\frac{1}{\text{Fraction of employed}_{ig}^{j}}\right)^{\frac{1+\xi}{\eta}}\exp\left[\frac{(1+\xi)\gamma_{em}}{\eta}\right],
\end{aligned}
$$

where γ_{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 $j=1,...,J$ can be expressed as:

$$
\begin{aligned}
n_{ig}^{j} = N_{ig}z_{ig}^{j}\left[(1/p)(1+\gamma_{ig}^{j}\nu_{g}^{j}\left(1-\tau_{g}^{j}-\kappa_{ig}^{j}\right)w_{ig}^{j}z_{ig}^{j}(1+s)\right]^{\xi} \\
\times\left(\text{Fraction of employed}_{ig}^{j}\right)^{\frac{\eta-(1+\xi)}{\eta}}\Gamma\left(1-\frac{1+\xi}{\eta}\right).
\end{aligned}
$$

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:

$$
\frac{\text{Earnings}_{ig}^{j}}{\text{Earnings}_{ig}^{k}} = \frac{\left[\left(1+\gamma_{ig}^{j}\right)\nu_{g}^{j}\right]^{\xi}\left[\left(1-\tau_{g}^{j}-\kappa_{ig}^{j}\right)w_{ig}^{j}z_{ig}^{j}\right]^{1+\xi}}{\left[\left(1+\gamma_{ig}^{k}\right)\nu_{g}^{k}\right]^{\xi}\left[\left(1-\tau_{g}^{k}-\kappa_{ig}^{k}\right)w_{ig}^{k}z_{ig}^{k}\right]^{1+\xi}}\left(\frac{\text{Fraction of employed}_{ig}^{k}}{\text{Fraction of employed}_{ig}^{j}}\right)^{\frac{1+\xi}{\eta}}.
$$

Plugging in the corresponding expressions for Fraction of employed$_{ig}^{j}$ and Fraction of employed$_{ig}^{k}$ 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 (3) by considering two worker (type, subtype) pairs (i,g) and (q,r) who choose a given occupation j:

$$
\frac{\text{Earnings}_{ig}^{j}}{\text{Earnings}_{qr}^{j}} = \frac{\left[\left(1+\gamma_{ig}^{j}\right)\nu_{g}^{j}\right]^{\xi}\left[\left(1-\tau_{g}^{j}-\kappa_{ig}^{j}\right)w_{ig}^{j}z_{ig}^{j}\right]^{1+\xi}}{\left[\left(1+\gamma_{qr}^{j}\right)\nu_{r}^{j}\right]^{\xi}\left[\left(1-\tau_{r}^{j}-\kappa_{qr}^{j}\right)w_{qr}^{j}z_{qr}^{j}\right]^{1+\xi}}\left(\frac{p_{qr}^{j}}{\text{Fraction of employed}_{ig}^{j}}\right)^{\frac{1+\xi}{\eta}}.
$$

We have that Equation (3) 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 λ of the weighted average of annual earnings across all market occupations for each (type, subtype).

Equation 3. We derive Equation (4) 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:

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

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

Equation 4. We derive Equation (5) 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:

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

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

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

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

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

Equation (5) results from combining these expressions where we set $q = 1$ (i.e., natives) which implies setting $\kappa_{qr}^j = 0$ 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 (6) 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 (5), (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

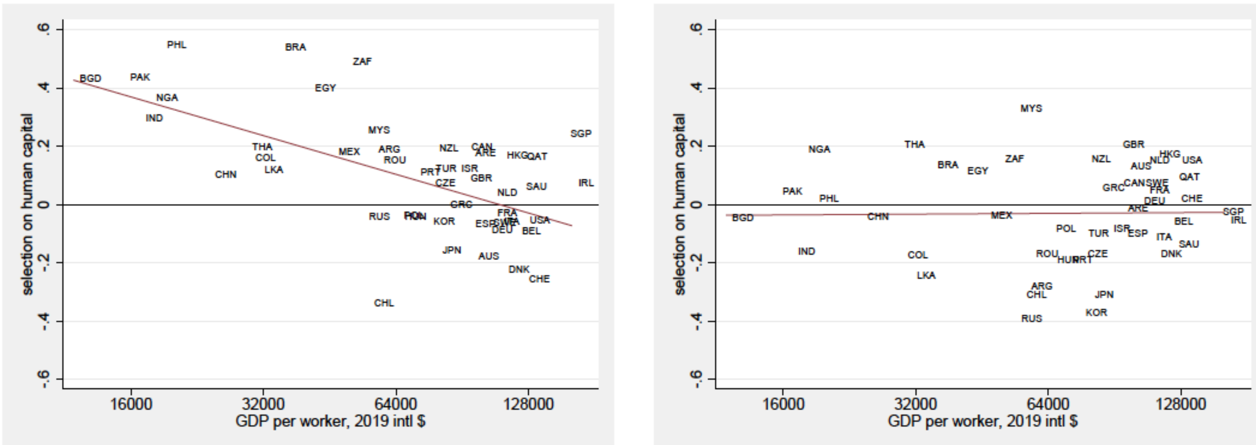
Average human capital across immigrants, emigrants, and non-migrants. In Section 3.2, we assume that the shape parameter η_i of the Frechet distribution of idiosyncratic productivities is the same for natives and immigrants. This assumption implies that immigrants and natives draw η_i from the same distribution.

This assumption is motivated by the recent evidence from Martellini, Schoellman, and Sockin (2023) on the average human capital of emigrants, immigrants, and non-migrants across countries. Panel (a) of Figure 4 of their paper (reproduced in Figure A5 for ease of reference) 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.

Panel (a) shows that emigrants are more positively selected when migrating from less-developed economies. 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 shape parameter η_i of the Frechet distribution of

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

(a) Emigrants (b) Immigrants



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).

idiosyncratic productivities is the same for natives and immigrants.

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.

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 4.3, 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

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

	Distribution						
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
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
	Annual earnings						
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
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
	Hourly wages						
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
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), $I_{\text{Low Eng}}$ denotes low English proficiency immigrants, $I_{\text{High Eng}}$ 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).

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

Table A4: Aggregate and sectoral effects of removing wedges: Within-market reallocation

Occupation type	Percent change Real GDP	TFP	Employment	Hours	Change in immigrant share (pp)
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	1.35
Non-routine manual	10.04	1.22	2.81	5.73	1.98
Routine cognitive	1.65	1.11	-1.04	1.59	-0.90
Routine manual	2.39	2.28	-3.98	4.25	-3.10

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.

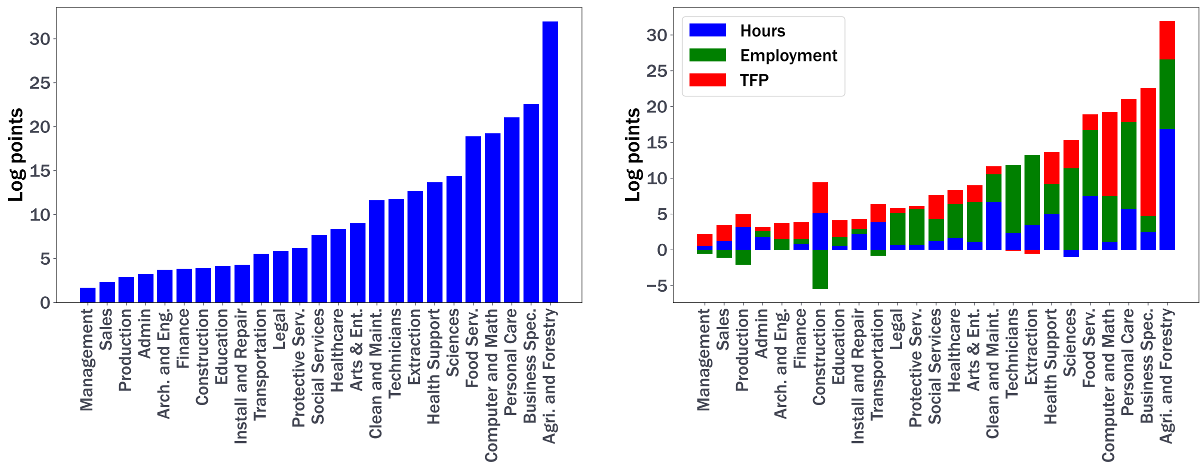
Role of within occupation transitions on GDP gains when immigrant wedges are removed. Table 5 in Section 4.3 documents the aggregate gains from removing immigrant wedges. These gains are obtained due to both flows of non-employed immigrants from the non-market occupation to market occupations and flows of employed immigrants within market occupations. To quantify the role of flows of immigrants between the non-market occupation and market occupations, in Panel B of Table A4, 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.

Effects of removing immigrant wedges across all occupations. Table 5 in Section 4.3 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

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

(a) Real GDP gains (b) Decomposition of sources of real GDP gains



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.

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.

Reallocation patterns across immigrants. The results reported in Table 5 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 A5 presents the distribution of worker reallocation patterns for immigrant type/subtypes, as discussed in Section 4.3. 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.

Table A5: 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.

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 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.

Removing immigrant wedges for each immigrant type/subtype. Table 6 in Section 4.4 presents the gains associated with removing immigrant wedges faced by specific immigrant types or subtypes. In order to provide further intuition for the results in Table 6, Table A6 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 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 A6: 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.

Table A6 is provided around Table 6 in the main text.

Removing immigrant wedges for each occupation. In Section 4.4, 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 A7 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.[7] Table

[7] 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 A7: Gains from removing immigrant wedges by occupation

Occupation type	Real GDP (% change)	Share of population (baseline level, %)	Real GDP growth 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.

A7 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.

Microeconomic elasticities: Model vs data. In Section 5.1, we compare elasticities of labor market moments for natives and existing immigrants to the Marielitos shock in the data and the model. Here, we provide details about the measurement of this elasticity in the empirical literature and how we implement this exercise using our model.

Empirical estimates. 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 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.

Table 7 in the text uses estimates in 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.

Model implementation. We use our model of the U.S. economy as our model of Miami upon the arrival of the Marielitos.[8] 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.[9]

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.

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 7. 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 A8. Overall,

[8] 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.

[9] 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.

Table A8: Gains from removing immigrant wedges under alternative parametrizations

	Percent change				Change in
	Real GDP	TFP	Employment	Hours	immigrant share (pp)
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.

our main results remain 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 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 $\sigma_j = 20 \quad \forall j = 1, ..., J$. 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 $\sigma_j = 4.6 \ \forall j = 1, ..., J$ 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 A8 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 $\sigma_j = 40 \;\; \forall j = 1, ..., J$, the same value we use to approximate perfect substitution in the inner nest with $\widetilde{\sigma}_j = 40 \; \forall j = 1, ..., J$. Because our baseline calibration with $\sigma_j = 20 \;\; \forall j = 1, ..., J$ 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 $\sigma_j = 40 \;\; \forall j = 1, ..., J$.

Fifth, in our estimation, we approximate the perfect substitution across labor bundles in the inner nest with $\widetilde{\sigma}_j = 40 \; \forall j = 1, ..., J$. Table A8 shows that our results remain similar under a higher value of this elasticity (i.e., $\widetilde{\sigma}_j = 80 \; \forall j = 1, ..., J$).

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.