Immigrant Misallocation*

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Abstract

We quantify the barriers that impede the economic integration of immigrants and investigate their aggregate implications. We develop a model of occupational choice with natives and immigrants of multiple types whose decisions are subject to wedges which distort their allocation across occupations. We estimate the model to match salient features of U.S. and cross-country individual-level data. We find that there are sizable GDP gains from removing the wedges faced by immigrants in U.S. labor markets, accounting for approximately one-tenth of the overall economic contribution of immigrants to the U.S. economy. These effects arise from both increased flows from non-participation to employment as well as from reallocation from manual towards cognitive jobs. We compare our findings across 19 developed and emerging economies and find substantial differences in the magnitude of immigrant wedges across countries. Importantly, we find that cross-country differences in immigrants' labor force participation and in the distribution of immigrant wedges across occupations with different productivities lead to substantial variation in the gains from removing the barriers to immigrant integration.

Keywords: Immigration, Occupational Barriers, Mobility, Misallocation
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1 Introduction

Increased immigration holds the potential to be an important source of increased economic well-being across countries (Clemens 2011). For instance, by boosting a country's labor supply, stock of human capital, and reducing dependency ratios, immigrants can have a potentially key impact on innovation, growth, and fiscal sustainability. Yet, immigrants often face severe barriers to integrate into foreign labor markets, preventing them from working in the occupations that they are most productive at. Immigrants' productive potential is often limited by occupational regulations and licensing (Peterson, Pandya, and Leblang 2014), lack of destination-specific skills (Moreno-Galbis and Tritah 2016), or discrimination (Oreopoulos 2011), among other barriers. While there is extensive micro-level evidence on various types of barriers faced by immigrants, understanding their relative importance and macroeconomic effects has remained elusive.

The goal of this paper is to quantify the aggregate and distributional implications of barriers that prevent immigrants from integrating into foreign labor markets. To do so, we set up a model of occupational choice á la Roy (1951) featuring natives and immigrants of multiple types, where we introduce wedges that distort the decisions of immigrants relative to their native counterparts. We interpret these wedges as capturing distortions that might impact immigrants' occupational choices. The model extends the quantitative framework developed by Hsieh, Hurst, Jones, and Klenow (2019) to modeling immigrants as in Burstein, Hanson, Tian, and Vogel (2020). We find that immigrant barriers in the U.S. are quantitatively large, exhibiting significant heterogeneity across worker types and occupations, and implying sizable real GDP gains from removing them.

Consistent with micro-level studies, our estimated immigrant barriers raise important questions about the economic opportunities faced by immigrants in the U.S. and their expected degree of economic mobility. For instance, we find that, while the estimated wedges in the U.S. are higher among recent immigrants, they remain quantitatively significant even across immigrants who have lived in the U.S. for at least 10 years. Similarly, while we find that immigrants with weak English proficiency experience larger immigrant barriers, even immigrants proficient in English are subject to severe barriers. Given our estimates of immigrant barriers in the U.S., we investigate their aggregate and distributional effects, and examine the implications of our findings for immigration policy and for cross-country differences in immigrant barriers.

This paper contributes to the literature along four dimensions. First, we show that the extensive barriers faced by immigrants previously documented in the literature lead to significant misallocation in the aggregate, with high potential real GDP gains from removing them. Second, we identify the key margins across occupations and worker types along which immigrant distortions are quantitatively the largest and most distortive in the aggregate. Third, we study the implications of immigrant barriers for immigration policy reform in a framework that we show is consistent with prior estimates of the labor market effects of changes in immigrant labor supply.

Fourth, we contrast our estimates of immigrant barriers for the U.S. and their implications by extending the analysis using data for 19 countries with nontrivial immigrant populations — we show that immigrant barriers are pervasive and often much larger than in the U.S. Critically, we identify key cross-country differences that account for such heterogeneity.

Our starting point is to set up a quantitative general equilibrium model populated by natives and immigrants that can be used to estimate immigrant barriers and to conduct counter-factual analyses. We consider a closed economy with natives and immigrants of multiple types who choose among alternative labor market occupations or to stay out of the labor force. Individuals differ across types in their productivity and in their preferences across occupations. And each occupation consists of a producer that hires workers of all types to produce an occupation-specific good. These goods are then aggregated to produce a final goods that is consumed by all individuals.

We model the role of immigrants in our economy as follows. First, we assume that immigrants are subject to immigrant barriers, which we model as immigrant-specific wedges. On the one hand, immigrants are subject to immigrant-specific compensation wedges, which we model as proportional taxes that can vary across occupations. On the other hand, immigrants are subject to immigrant-specific labor supply wedges, which distort their choices across occupations given compensation and preferences.[1] Second, we assume that the production of occupation-specific goods features imperfect substitution between native and immigrant workers, as estimated by Burstein et al. (2020) and others.

We interpret immigrant wedges as capturing the wide range of barriers faced by immigrants in foreign labor markets, as previously documented in the literature. In the model, immigrant wedges distort the occupational choices of immigrants relative to their native-counterparts along two key margins. First, they discourage immigrants from working in market occupations, generating elevated non-participation rates. Second, they prevent the allocation of immigrants in the market sector to their most productive occupations, leading to misallocation, reducing aggregate output and productivity.

We show that all the key parameters of the model, including all wedges and worker productivity, can be estimated to exactly match the joint distribution of employment and earnings across worker types and occupations. In particular, we derive analytical expressions to mechanically back out the estimated parameters given a very limited set of predetermined parameters and widely accessible data. This approach ensures the estimation of the model with rich levels of heterogeneity, and also allows us to obtain sharp insights on the patterns of the data that identify the various wedges and worker productivity.

To characterize the magnitude and distribution of immigrant wedges in the U.S., we esti-

[1] Additionally, individuals are subject to compensation wedges that differ across worker characteristics but which are independent of immigration status.

mate the model using individual-level data from the American Community Survey (ACS) across natives and immigrants of multiple types. Given the approach described above, we match the joint distribution of employment and earnings across worker types and occupations in the U.S. We consider multiple types of immigrants partitioned based on time since immigration, English language skills, and income level of the country of origin. We further partition natives and all immigrant types into subtypes based on education, age, and gender. We classify occupations into four groups based on their skill and task-intensity, following Acemoglu and Autor (2011), David and Dorn (2013), and Cortes, Jaimovich, Nekarda, and Siu (2020). These disaggregate worker groups allow us to estimate immigrant wedges across occupations accounting for demographic and immigrant characteristics.

We find that the estimated wedges are quantitatively large and vary systematically across worker types and occupations. For instance, immigrants are subject to severe barriers to work in cognitive occupations, facing substantially lower barriers to work in manual occupations. We also find that immigrant barriers vary systematically by time since immigration or English proficiency: Recent immigrants and ones with poor English skills are estimated to face larger barriers. These patterns are intuitive and consistent with previous studies, pointing to the challenges faced by new immigrants to integrate and be productive in their host country.

To evaluate the aggregate implications of the barriers faced by immigrants in U.S. labor markets we conduct the following experiment. We contrast our estimated model of the U.S. economy with a counterfactual economy in which immigrants are not subject to immigrant barriers. We find that removing immigrant wedges increases real GDP by 2.63 percent. This output increase results from reallocation along two margins: an increase of labor force participation among immigrants and a reallocation of employed immigrants into more productive jobs. On the one hand, the entry of immigrants into the labor force increases their total labor supply, especially into cognitive jobs. On the other hand, the reallocation of immigrants across occupations leads to a modest productivity decrease in cognitive jobs due to the inflow of workers who are relatively less productive than those who were already choosing these jobs *despite* the presence of large wedges. In contrast, the outflow of workers away from manual jobs leads to an increase in average productivity for these occupation types.

To put these findings in context, we contrast the effect of removing immigrant barriers on real GDP relative to the overall contribution of immigrants to the U.S. economy. To compute the latter, we contrast our baseline model with a counter-factual economy without immigrants, and interpret the real GDP difference between them as capturing the contribution of immigrants. We find that the gains from removing immigrant barriers are 6.18% of the total contribution of immigrants to U.S. economic activity.

We also show that the aggregate implications of removing immigrant barriers differ substantially across worker types and occupations. To do so, we consider a series of experiments in which we contrast our estimated model of the U.S. economy relative to counterfactual economies in which wedges are removed one-at-a-time for specific worker types or occupations. These exercises reveal that larger real GDP gains per immigrant result from removing the wedges faced by recent immigrants, those who are female, as well as those with degrees in STEM and the social sciences. We also find substantially smaller gains from removing immigrant barriers in non-routine manual occupations. These findings show that the implications of immigrant barriers are heterogeneous across worker types and occupations, suggesting that policies designed to remove them might be more effective if targeted on certain subsets of the population.

Next, we investigate various implications of our main findings. We first study their implications for the design of immigration policy in the U.S., and then we investigate the extent and effects of immigrant misallocation across countries.

To investigate the implications of our findings for immigration policy, we ask: How does the output per worker gains from admitting new immigrants into the U.S. differ across immigrant types, and how are these returns determined by immigrant barriers? Importantly, the output and productivity effects of increased immigration fundamentally depend on how new immigrants affect the allocations and earnings of natives and previous immigrants. Thus, before evaluating alternative immigration policies, we first contrast the model's implications for the labor outcomes of natives and previous immigrants following an increase in the stock of immigrants vis-a-vis their empirical counterpart.

We contrast our model's implications relative to empirical studies that analyze the effects of the inflow of Cuban immigrants to Miami in 1980 on labor market outcomes of natives and immigrants. To do so, we consider a similar inflow of immigrants in our model, with the same characteristics as the set of Cuban immigrants who arrive to Miami in 1980, and study its implications. Consistent with a broad set of empirical studies, we find that the inflow of Cuban immigrants had limited effects on the labor market effects of natives but larger effects on wages of immigrants in Miami. The limited impact on natives is largely driven by the imperfect substitution between natives and immigrants in the production of occupation-specific goods. In contrast, the average wages of immigrants decline in the model after the immigrant shock because (i) the newly admitted immigrants are pre-dominantly less-educated and they select to work in low-paying occupations, and (ii) immigrants are perfectly substitutable between, leading to a decline in wages of immigrants when their labor supply increases.

With a model that can consistently account for empirical estimates of the effects of increased immigration on labor market outcomes, we then use it to study the impact of alternative policies to increase immigration into the U.S. In particular, we study the impact of increasing the mass of immigrants in our model, contrasting alternative compositions of the set of new immigrants. We find that immigration policies biased toward immigrants with a college degree, especially with a STEM field akin to the H1B visa policy in the U.S., lead to significant increases in output per worker. On the other hand, output per worker declines in response to immigration policies that admit immigrants without a college degree or immigrants who are not fluent in English. Importantly, we show that these gains and losses are amplified in the absence of immigrant barriers.

Finally, we contrast our findings on the extent and impact of immigrant barriers in the U.S. relative to other countries with significant immigrant populations. To do so, we use the Luxembourg Income Study (LIS) to combine and harmonize individual-level data from labor force surveys for 19 economies. We use these cross-country microdata to estimate the model for each country following the same approach as for the U.S. We then use these estimated models to contrast immigrant wedges across countries as well as their aggregate implications. We find that there is substantial heterogeneity in the magnitude and impact of the barriers faced by immigrants across countries. For instance, countries such as the U.K. or Australia are estimated to feature low immigrant wedges and effects on average, while these are much higher in some European countries like Belgium, Netherlands, and Spain. We find that the U.S. features immigrant wedges and effects from removing them that are close to the average across the countries in our sample.

While the average magnitude of immigrant barriers is tightly connected with the implied gains from removing them, we also find non-trivial heterogeneity in their impact even across countries with similar immigrant barriers. We show that much of this cross-country heterogeneity in the gains from removing immigrant wedges is accounted by two key cross-country differences. Along the extensive margin, we find that countries with a higher fraction of immigrants out of the labor force feature significantly larger gains from removing immigrant wedges. Along the intensive margin, we find that the correlation between wedges and occupational productivity also plays an important role. That is, the gains from removing immigrant wedges are larger in economies in which these wedges are relatively larger in productive occupations.

To summarize, our findings show that immigration barriers are pervasive in both the U.S. as well as across countries, with potentially sizable real GDP gains from removing them. Moreover, our findings have important implications for the design of both labor market and immigration policy. On the one hand, we find that labor market policies designed to alleviate immigrant barriers on targeted subsets of the immigration population, such as recent immigrants or ones with poor langugage skills, can be relatively more effective per immigrant than blanket policies targeted at the broad immigrant population. On the other hand, we find that the gains from immigration policy reform that increases immigration vary in effectiveness depending on both the intrinsic characteristics of immigrants and the immigrant barriers faced upon arrival. These findings suggest that considering reforms of labor market and immigration policies jointly might be desirable to maximize their aggregate impact.

This paper contributes to an extensive literature that studies differences in the labor market experience of natives and immigrants. Immigrants have been documented to be at a disadvantage in foreign labor markets due to occupational regulations and licensing (Peterson, Pandya, and Leblang 2014), having lower bargaining power against employers (Moreno-Galbis and Tritah 2016), being subject to discriminatory practices among recruiters (Oreopoulos 2011), facing initial gaps in complementary skills and skills mismatch that results in downgrading (Eckstein and Weiss 2004; Dustmann, Frattini, and Preston 2013), the slowing pace of labor market assimilation (Albert, Glitz, and Llull 2020), and cultural factors (Antecol 2000), among many other factors. These barriers lead to immigrants' poorer performance and outcomes in host countries' labor markets (Abramitzky and Boustan 2017; Arellano-Bover and San 2020; Dostie, Li, Card, and Parent 2020; Albert and Monras 2018). Our paper complements these studies by quantifying the macroeconomic effects of immigrant misallocation that result from these barriers. Our approach relies on using microdata to identify key dimensions of heterogeneity in the size of immigrant wedges across demographics and occupations, and importantly, demonstrates how the distribution of immigrant wedges affects key aggregates such as output, employment, productivity, wages, and labor market allocations.

Our paper also contributes to a broader 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 represent an increasing share of employment in host countries. We show that immigrants face substantial wedges that distort their occupation decisions, with significant implications for aggregate outcomes.

This paper is organized as follows. Section 2 presents our model. Section 3 provides details on the data and estimation approach, and presents the estimation results. Section 4 shows and discusses our findings for the U.S and Section 5 studies immigrant wedges and their aggregate implications across countries. Section 6 concludes.

2 Model

We consider an economy populated by a continuum of individuals and a discrete number of occupations $j = 0, ..., J$. Individuals choose an occupation in which to work, 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 consumed by individuals. Below, we describe the economic environment in which these agents operate and then define a competitive equilibrium of this economy.

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, recent immigrants, established immigrants).[2] 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 denoted by $N = \sum_{i=1}^{I} \sum_{g=1}^{G} N_{ig}$.

Preferences and immigrant labor supply wedges Individuals of type i and subtype g who choose to work in occupation j have preferences over consumption of the final good that are represented by the following utility function:

$$u_{ig}^{j}(c) = (1 + \gamma_{ig}^{j})\nu_{g}^{j} c,$$

where ν_g^j is a preference shifter that is common across all individuals of subtype g who choose to 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 $\gamma_{1,g}^j = 0 \; \forall g, j$ since $i = 1$ denotes native individuals. We refer to γ as a "immigrant labor supply wedge" since it distorts immigrants' labor supply decisions across occupations relative to natives. We introduce these wedges to investigate the extent to which immigrants' labor supply decisions across occupations are distorted. We study their implications on equilibrium allocations in the following sections.

Labor productivity across occupations Individuals are endowed with one unit of labor that they supply to an occupation j, but individuals are not equally productive in all occupations. An individual of type i and subtype g who chooses to work in occupation j is endowed with $z_{ig}\varepsilon_j$ effective units of labor, where z_{ig} is a productivity component common across all individuals of type i and subtype g, while ε_j is an idiosyncratic occupation-specific productivity draw.

In particular, each individual of type i and subtype g is characterized by a vector of idiosyncratic productivities $(\varepsilon_0, ..., \varepsilon_J)$ for each of the occupations in the economy. Each of these idiosyncratic productivities is distributed Frechet with scale parameter η and are *i.i.d.* within individuals as well as across individuals of all types and subtypes. The joint cumulative distribution function (CDF) is thus given by $F(\varepsilon_0, ..., \varepsilon_j) = \exp\left(\sum_{j=0}^{J} \varepsilon_j^{-\eta}\right)$.

Labor income and compensation wedges Individuals of type i and subtype g who work in occupation j are paid a wage rate 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

[2]In the quantitative analysis, we further partition immigrants based on their language skills as well as their country of origin.

compensation wedges as proportional taxes (or subsidies) on the labor income of individuals. All individuals of subtype g that choose to 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, we have that $\kappa_{1,g}^j = 0 \ \forall g, j$ 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.[3]

Problem of individuals The problem of an individual of type i and subtype g consists of maximizing utility by choosing the occupation j in which to work subject to a budget constraint. In particular, an individual of type i and subtype g with vector of idiosyncratic productivities $(\varepsilon_0, ..., \varepsilon_J)$ chooses the occupation j^* that solves the following problem:

$$\begin{aligned}&\max_{j=0,\dots,J} (1+\gamma_{ig}^j)\nu_g^j c \\ &\text{subject to} \\ &pc = (1-\tau_g^j - \kappa_{ig}^j) w_{ig}^j z_{ig} \varepsilon_j \times (1+s),\end{aligned}$$

where p denotes the price of final goods. The right-hand-side of the budget constraint denotes the labor income of individuals net of compensation wedges τ_g^j and κ_{ig}^j, along with reimbursement s; the left-hand-side shows individuals spend all their net income on consumption of final goods.

2.2 Occupations

Production in each occupation $j = 0, ..., J$ is carried out by an occupation-specific representative firm. We refer to occupation $j = 0$ as denoting non-market occupations or work at home. We refer to the rest of the occupations $j = 1, ..., J$ as market occupations that capture workers employed in the labor market.

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) production technology that aggregates the different types of labor in the economy to produce an occupation-specific good. In contrast, production in non-market occupations is carried out through a linear (constant returns to scale) technology, allowing us to capture the idea that non-market occupations may encompass home production activities that could be carried out independently by each individual.[4]

[3] Allocations remain unchanged if we instead consider the remibursement of wedges via lump-sum transfers.

[4] Specifically, while we consider an aggregate linear technology in non-market occupations, the equilibrium allocations are identical to those from an economy in which such technology is operated independently by each individual who chooses such occupations.

2.2.1 Market occupations

Production in each market occupation $j = 1, ..., J$ is carried out by a representative firm. Following Burstein, Hanson, Tian, and Vogel (2020), the production technology is 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 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 workers across types and subtypes based on demographic characteristics such as age, gender, and education within a given group based on immigration status (e.g., natives, immigrants).

Outer nest: Aggregation between natives and immigrants The production technology for the outer nest aggregates worker bundles between natives and immigrants with a constant elasticity of substitution σ_j:

$$y_j = A_j \left[n_{\text{nat}}^{j\ \frac{\sigma_j - 1}{\sigma_j}} + n_{\text{imm}}^{j\ \frac{\sigma_j - 1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j - 1}},$$

where y_j denotes the total output produced by occupation j, n_k^j denotes the labor bundle of group k in occupation j, and A_j denotes occupation-specific productivity. We index the group of natives and immigrants with subscripts $k = \text{nat}$ and $k = \text{imm}$, respectively.

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 then given by:

$$\begin{aligned} &\max_{y_j, n_{\text{nat}}^j, n_{\text{imm}}^j} \ p_j y_j - w_{\text{nat}}^j n_{\text{nat}}^j - w_{\text{imm}}^j n_{\text{imm}}^j \\ &\text{subject to} \\ &y_j = A_j \left[n_{\text{nat}}^{j\ \frac{\sigma_j - 1}{\sigma_j}} + n_{\text{imm}}^{j\ \frac{\sigma_j - 1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j - 1}}, \end{aligned}$$

where p_j denotes the price of the goods produced by occupation j, n_k^j and w_k^j denote the amount and the cost of labor bundle $k \in \{\text{nat,imm}\}$ hired by occupation j, respectively.

Inner nest: Aggregation within natives and immigrants The production technology for the inner nest produces worker 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 constant elasticity of substitution σ_{kj}, where $\mathcal{I}_{\text{nat}} = \{1\}$

and $\mathcal{I}_{\text{imm}} = \{2, ..., I\}$:

$$n_k^j = \left[\sum_{i \in \mathcal{I}_k} \sum_{g=1}^{G} n_{ig}^{j \, \frac{\tilde{\sigma}_j - 1}{\tilde{\sigma}_j}} \right]^{\frac{\tilde{\sigma}_j}{\tilde{\sigma}_j - 1}},$$

where n_k^j denotes the labor bundle of group k in occupation j and n_{ig}^j denotes the effective units of labor hired from individuals of type i and subtype g.

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 their wage rate in occupation j. The problem is then given by:

$$\begin{aligned}
&\max_{n_k^j, \{n_{ig}^j\}_{i \in \mathcal{I}_k, g}} w_k^j n_k^j - \sum_{i \in \mathcal{I}_k} \sum_{g=1}^{G} w_{ig}^j n_{ig}^j \\
&\text{subject to} \\
&n_k^j = \left[\sum_{i \in \mathcal{I}_k} \sum_{g=1}^{G} n_{ig}^{j \, \frac{\tilde{\sigma}_j - 1}{\tilde{\sigma}_j}} \right]^{\frac{\tilde{\sigma}_j}{\tilde{\sigma}_j - 1}},
\end{aligned}$$

where w_{ig}^j denotes the wage rate per effective units of labor for individuals of type i and subtype 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 hired, with occupation-specific productivity A_0.

The problem of the representative producer in the non-market occupation consists of maximizing profits by choosing the total effective units of labor hired given the price of the good sold as well as the occupation-specific wage rate w^0. The problem is then given by:

$$\begin{aligned}
&\max_{y^0, n^0} p_0 y_0 - w^0 n^0 \\
&\text{subject to} \\
&y_0 = A_0 n^0.
\end{aligned}$$

2.3 Final good producer

Final goods are produced by a representative firm that aggregates the goods produced across all occupations by operating a constant elasticity of substitution technology with elasticity σ.

The problem of the representative producer of final goods consists of maximizing profits by choosing the amount of goods to purchase from each of the occupations, taking as given the price of final goods as well as the price of the goods produced across all occupations. The problem is then given by:

$$\max_{y,\{y_j\}_{j=0}^{J}} py - \sum_{j=0}^{J} p_j y_j$$

subject to

$$y = \left[\sum_{j=0}^{J} y_j^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

2.4 Equilibrium

Let each individual's idiosyncratic productivity vector be denoted by ω, and let $\varphi(\omega)$ denote the probability density function of individuals with vector ω. Let the occupation choice of an individual of type i, subtype g, and idiosyncratic productivity vector ω, be denoted by $\mathcal{O}_{ig}(\omega) \in \{1, ..., J\}$.

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

1. Given price p and wages $\{w_{ig}^j\}_{j=0}^{J}$, $\mathcal{O}_{ig}(\omega)$ solves the problem of each individual of type i, subtype g, and productivity vector ω

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 $\{w_{ig}^j\}_g$, n_k^j and $\{n_{ig}^j\}_g$ 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 $\{p_j\}_{j=0}^{J}$, $\{y_j\}_{j=0}^{J}$ solve the problem of final good producers

6. Government's budget constraint holds:

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

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

$$n_{ig}^{j} = N_{ig} \times \int z_{ig}\varepsilon_j(\omega)\mathbf{I}_{\{j=\mathcal{O}_{ig}(\omega)\}}\varphi(\omega)d\omega$$

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

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

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

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, implicitly assuming that the same values that solve the problem of occupational good producers also solve the problem of final good producers.

3 Estimation

We now proceed to investigate the extent to which immigrant wedges distort the allocation of immigrants, and their aggregate and distributional implications. In this section, we describe our estimation approach, and in the following section we present our main findings.

3.1 Data

We estimate the model using U.S. data from the 2019 American Community Survey (ACS). We restrict our sample to non-business owner individuals between the ages of 25 and 54. This sample restriction allows us to focus on working age individuals, after they finish schooling and prior to retirement. We also drop individuals who are not on active military duty. Appendix A.1 provides details about the data, construction of variables, and measurement.

Individual types We begin by partitioning individuals in the data into the I types of individuals featured by 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 their home country's income level. We define immigrants as the set of foreign-born individuals.[5]

We partition immigrants' time since immigration based on their reported years since moving into the U.S. Immigrants with no more than 10 years since immigration are classified as "recent immigrants" and immigrants whose years since immigration is higher than 10 years are classified as "established immigrants." We partition immigrants' English proficiency based on the

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

self-reported assessment collected by the ACS. We consider three English fluency groups: cannot speak, speaks but not well, and speaks well. Finally, we partition the level of economic development of the immigrants' native country by combining information on each respondent's country of birth collected by the ACS with data on each country's gross national income per capita for 2019. We group countries into three groups: low-income, middle-income, and high-income countries.

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

Individual subtypes We then further partition individuals in the data of each individual type $i = 1, ..., I$ into G subtypes based on their level of education, age, and gender — we index subtypes by $g = 1, ..., G$.

We classify individuals by gender into two groups: male and female. We classify individuals by education into four groups: one group for those with less than a college degree and three groups for college graduates with degrees classified as either STEM, Law or Medical, or Social Sciences, Humanities, and Other. For age, we consider three groups: 25-34, 35-44, and 45-54.

As a result, we partition each set of individuals of type $i = 1, ..., I$ into 24 subtypes ($G = 24$) along the aforementioned dimensions: 2 (gender) $\times$ 4 (education) $\times$ 3 (age). Thus, we classify each individual observed in the data into one of a total of 456 worker (type, subtype) pairs.

Our disaggregation of workers into detailed types and subtypes is key in allowing us to estimate differential labor market outcomes and wedges across individuals. For instance, immigrants who have recently arrived to the U.S. may face larger barriers than those who have spent a longer time acclimating and integration into the U.S. labor market. Moreover, even among recent immigrants, differences in English fluency, home country, age, gender, and education may affect the extent to which the labor market allocation of immigrants is distorted relative to their native counterparts. In the following sections we investigate the role of these various dimensions of heterogeneity on the extent of immigrant misallocation.

Market vs. non-market occupations We allocate individuals between non-market ($j = 0$) and market ($j = 1, ..., J$) occupations following Hsieh, Hurst, Jones, and Klenow (2019). We classify an individual as being in the non-market occupation if she is not currently employed or if she is currently employed but usually works less than 10 hours per week. A currently-employed individual who usually works more than 30 hours per week is assigned to one of the market occupations defined below. Finally, currently-employed individuals who usually work between 10 and 30 hours per week are classified as part-time workers. For any part-time workers, we divide their sample weight equally between the non-market and market occupations.

Market occupations We partition employed individuals into J market occupations based on Standard Occupational Classification (SOC) codes, as collected by the ACS — we index the occupations of employed individuals by $j = 1, ..., J$.

We consider four occupational groups ($J = 4$) based on the skills and types of tasks involved. To do so, we classify occupations following Acemoglu and Autor (2011), David and Dorn (2013), and Cortes, Jaimovich, Nekarda, and Siu (2020) into: routine manual, routine cognitive, non-routine manual, and non-routine cognitive. In particular, routine manual occupations are Production, Craft and Repair Occupations, Operators, and Transportation and Material Moving Occupations; routine cognitive are Sales and Clerical Occupations; non-routine manual are Service Occupations; and non-routine cognitive occupations are Professional, Managerial and Technical Occupations.[6]

Earnings We measure the earnings of individuals as total annual labor income of the respondent in the ACS. For each set of individuals of type i and subtype g in market occupation j, we compute the group's average annual earnings as a geometric average among currently employed individuals with non-missing labor earnings information. For each worker (type, subtype) pair, we set the labor income in the non-market occupation to be a fraction λ of the weighted average income across all market occupations. In particular, we set $\lambda = 0.50$ motivated by the 50 percent unemployment insurance (UI) replacement rate in the U.S.

Summary statistics Table 1 presents summary statistics on the distribution of individuals across market and non-market occupations and their associated earnings. We present here moments for alternative individual types, aggregating across subtypes. In Section 3.2 we present our approach to estimating the model to match analogous moments for each type-subtype pair in each occupation.

The top panel of Table 1 presents the distribution of individuals across market occupations for alternative types of individuals. The first column reports the distribution of natives across occupations, while the remaining columns report the analogous distribution for alternative types of immigrants. Consider the distribution of immigrants by time since immigration, as reported in the second and third columns. We observe that, while recent immigrants work in a wide range of occupations, they are significantly less likely to work in market occupations than established immigrants (27% vs. 35%, respectively). In addition, we find that both recent and established immigrants are more likely to work in manual occupations than their native counterparts.

Moreover, we observe that English proficiency and the level of economic development of immigrants' source country also appear to be systematically related to their occupations. Comparing the fourth and fifth columns of the table, we observe that immigrants with high English proficiency are much more likely to work in cognitive occupations and much less likely to be out

[6]Table A1 provides SOC codes and example occupations for each categories of these broad occupation groups.

Table 1: Empirical moments

Occupation Type	Distribution						
	N	I_{0-10}	I_{10+}	$\mathrm{I}_{\text{Low Eng}}$	$\mathrm{I}_{\text{High Eng}}$	I_{LIC}	I_{HIC}
Non-routine, Cognitive	0.34	0.28	0.27	0.03	0.35	0.37	0.45
Non-routine, Manual	0.10	0.13	0.14	0.18	0.12	0.12	0.07
Routine, Cognitive	0.15	0.08	0.11	0.04	0.12	0.10	0.12
Routine, Manual	0.14	0.16	0.20	0.28	0.16	0.12	0.08
Home	0.27	0.35	0.27	0.46	0.26	0.28	0.28
	Earnings						
Occupation Type	N	I_{0-10}	I_{10+}	$\mathrm{I}_{\text{Low Eng}}$	$\mathrm{I}_{\text{High Eng}}$	I_{LIC}	I_{HIC}
Non-routine, Cognitive	1.53	1.62	1.88	1.15	1.83	1.89	2.05
Non-routine, Manual	0.69	0.52	0.62	0.48	0.64	0.61	0.69
Routine, Cognitive	0.93	0.75	0.91	0.60	0.90	0.86	1.13
Routine, Manual	0.95	0.68	0.84	0.62	0.87	0.79	1.03
Home	0.49	0.42	0.46	0.26	0.52	0.50	0.63

Note: This table presents the employment distribution, annual income, and hourly income across different worker and occupations types. Values are based on a sample of non business owner individuals age 25–54 from the 2015-2019 CPS and averaged over educational attainment. The employment distribution across occupations is conditional on each worker type i. Earnings are all expressed as a multiple of values for a base subtype (prime-age, male, non-college natives) and occupation (non-routine cognitive). N denotes natives, I_{0-10} denotes recent immigrants ($\leq$ 10 years), I_{10+} denotes established immigrants (>10 years), $\mathrm{I}_{\text{Low Eng}}$ denotes low English proficiency immigrants, $\mathrm{I}_{\text{High Eng}}$ denotes high English proficiency immigrants, I_{LIC} denotes immigrants originating from low income countries, and I_{HIC} denotes immigrants originating from high income countries.

of the labor force. Comparing the sixth and seventh columns, we also find that immigrants from developed economies are more likely to work in cognitive occupations.

Table 1 also reveals significant earnings heterogeneity across individual types and occupations. Critically, the bottom panel of the table shows that immigrants appear to have systematically lower earnings than natives in all except non-routine cognitive occupations. Interestingly, we find that higher time since immigration, higher English proficiency, and higher economic development of the immigrants' source country are all associated with higher earnings.

To summarize, the observations above show that immigrants differ systematically from their native counterparts in their allocation across occupations as well as in their average earnings in these occupations. To what extent are these differences in the labor market outcomes of immigrants accounted by differences in their fundamentals (e.g., preferences, productivity, etc.) or by frictions faced by immigrants in the U.S. (e.g., immigrant compensation wedges, immigrant labor supply wedges)? We investigate this and other related questions in the following sections.

3.2 Estimation approach

We now present our approach to estimating the parameters of the model. To do so, we partition the parameter space into two groups. On the one hand, we have a set of parameters

Table 2: Estimation approach: Parameters and targets

Predetermined Parameters

Parameter	Value	Description
η	4	Frechet shape
σ	4.6	Elasticity across sectoral goods
$\{\sigma_j\}_{j=1}^J$	4.6	Elasticity across groups of worker types
$\{\widetilde{\sigma}_j\}_{j=1}^J$	100	Elasticity across worker subtypes

Estimated Parameters

Parameter	# of Parameters	Description	Normalization
$\{z_{ig}\}$	455	Worker productivity	$z_{b,\ell} = 1$
$\{\tau_g^j\}$	92	Compensation wedges	$\tau_\ell^j = 0\ \forall j,\ \tau_g^0 = 0\ \forall g$
$\{\kappa_{ig}^j\}$	1728	Immigrant compensation wedges	$\kappa_{1,g}^j = 0\ \forall g, j,\ \kappa_{ig}^0 = 0\ \forall i, g$
$\{\nu_g^j\}$	96	Preferences	$\nu_g^0 = 1\ \forall g$
$\{\gamma_{ig}^j\}$	1728	Immigrant labor supply wedges	$\gamma_{1,g}^j = 0\ \forall g, j,\ \gamma_{ig}^0 = 0\ \forall i, g$
$\{N_{ig}\}$	455	Mass of workers	$\sum_{i,g} N_{ig} = 1$
$\{A_j\}$	4	Occupation productivity	$A_1 = 1$
Total	4558		

Target Moments

Moment	# of Moments
Share of agents (i, g) that work in occupation $j\ \forall i, g, j$	2279
Avg. annual income of (i, g) in j relative to $(1, 1)$ in occupation $1\ \forall i, g, j$	2279
Total	4558

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

that are predetermined and set to standard values from the literature. On the other hand, we have a set of parameters that we estimate to match salient features of the data. Table 2 summarizes our estimation approach, listing the predetermined and estimated parameters, and the moments used to pin down the latter.

The set of predetermined parameters consists of η, σ, $\{\sigma_j\}_{j=1}^J$, and $\{\widetilde{\sigma}_j\}_{j=1}^J$. We set the shape parameter of the Frechet distribution η to 4, a common value in the literature. We set $\sigma_j = \sigma \quad \forall j = 1, ..., J$ to simplify the estimation as it allows us to analytically back out the model's parameters given the target moments. Following Burstein, Hanson, Tian, and Vogel (2020), we set the elasticity of substitution between natives and immigrants to 4.6. Thus, we have that $\sigma_j = \sigma = 4.6 \ \ \forall j = 1, ..., J$. In addition, we approximate perfect substitution in the inner nest across labor bundles within natives and immigrants by setting $\widetilde{\sigma}_j = 100 \;\; \forall j = 1, ..., J$. Our findings are robust to relaxing these assumptions.

Our first step to pinning down the estimated parameters is to make a set of normalizations and identifying assumptions. We begin by defining an individual base (type, subtype) pair as indexed by $b \in \{1, ..., I\}$ and $\ell \in \{1, ..., G\}$, respectively. Our first normalization consists of setting $z_{b,\ell} = 1$. This implies that the productivity of all other individual types and subtypes is expressed relative to the productivity of the base worker type and subtype (b, ℓ). Second, we assume that workers of all types and subtypes face no compensation wedges to choose the non-market occupation: $\tau_g^0 = 0$ and $\kappa_{ig}^0 = 0 \; \forall i, g$. We also assume that natives that belong to base type and subtype (b, ℓ) face no wedges to work in any of the market occupations: $\tau_\ell^j = 0$ $\forall j$. Thus, we assume that choosing to stay non-employed is not subject to frictions, and that natives that belong to the base type and subtype are not subject to frictions when choosing their market occupations. Third, we normalize the preference for non-market occupations such that $\nu_g^0 = 1 \; \forall g$. Fourth, we set immigrant labor supply wedges to be equal to zero in the non-market occupation: $\gamma_{ig}^0 = 0 \; \forall i, g$. Fifth, we normalize the total mass of all worker types to be 1 and the productivity of the first occupation A_1 to be 1. Finally, as defined in Section 2, we have that immigrant compensation and labor supply wedges are equal to zero for natives: $\gamma_{1,g}^j = 0 \; \forall g, j$ and $\kappa_{1,g}^j = 0 \; \forall g, j$.

We use the remaining parameters to target the share of workers (i, g) that work in occupation $j \; \forall i, g, j$, and the average earnings of worker (i, g) that work in occupation j relative to the average earnings of the base individual type and subtype (b, ℓ) in occupation $j = 1$. Throughout the rest of the paper, we set the base individual type and subtype to be given by natives that are male, 25 to 34 years old, and without a college degree.

3.3 Identification

Given the previously described predetermined parameters, normalizations, and target moments, we can analytically back out the remaining parameters directly from the data. Our goal in this section is to describe our approach to backing out the parameters of the model given our empirical targets, as well as to investigate the features of the data that pin down each parameter. For analytical tractability, we focus on the case of perfect subtitution across workers in the inner nest: $\widetilde{\sigma}_j = \infty \; \forall j = 1, ..., J$.

Population mass Given that we target the joint distribution of individuals across (type, subtype) pairs and occupations, we choose the mass of workers N_{ig} of each type and subtype (i, g) to match the respective fraction of individuals observed in the data with such characteristics. In the model, recall that the share of individuals of each type and subtype (i, g) is exogenous.

Thus, for each (i, g) pair we directly set:

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

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

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

where $\text{Earnings}_{ig,j}$ is given by the geometric average earnings across all individuals of type and subtype (i, g) in occupation j.

Given that immigrant labor supply wedges are zero for natives and that the preference for the home sector is normalized to one, we then have that preferences can be backed out from:

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

where recall that $i = 1$ denotes native individuals, and $\text{Avg. market earnings}_{ig}$ denotes the weighted average of $\text{Earnings}_{ig,j}$ across market occupations j with weights given by the share of individuals of such type and subtype that choose each market occupation. That is, the earnings of native individuals of subtype g in a given occupation j relative to the weighted average earnings of this type-subtype pair across all occupations is informative about their preference for occupation j.[7]

Given preferences $\{\nu_g^j\}_{g,j}$ and our normalization that the home sector and natives are not subject to immigrant labor supply wedges, we can back out these wedges for every immigrant type and subtype (i, g) in market occupation j as follows:

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

That is, immigrant compensation wedges in occupation j are identified by comparing the earnings of immigrants of type (i, g) in occupation j relative to average earnings across market occupations vis-a-vis the earnings of natives of subtype g in occupation j relative to their average earnings across market occupations.

For instance, consider immigrants of some given type i and subtype g whose earnings in occupation j are much lower than their average earnings across market occupations. If their native

[7]As described above, $\lambda = 0.50$ denotes the fraction of average income across market occupations that individuals earn in the non-market occupation.

counterparts of subtype g earn more in occupation j than their average earnings across market occupations, then the model interprets the lower relative earnings of immigrants in occupation j as accounted by immigrant labor supply wedges faced by immigrants in this occupation.

Critically, note that these implications are based on the equilibrium outcomes of the model, so implicitly control for other differences between natives and immigrants, such as differences in productivity or immigrant compensation wedges.

Worker productivity Consider individual type-subtype pairs (i, g) and (q, r), along with some occupation j. The solution of the model implies that:

$$\frac{z_{ig}}{z_{qr}} = \left(\frac{p_{ig,j}}{p_{qr,j}}\right)^{\frac{1}{\eta}} \frac{w_{qr}^{j}\,(1-\tau_{r}^{j}-\kappa_{qr}^{j})\ \text{Earnings}_{ig,j}}{w_{ig}^{j}\,(1-\tau_{g}^{j}-\kappa_{ig}^{j})\ \text{Earnings}_{qr,j}},$$

where $p_{ig,j}$ denotes the fraction of individuals of type (i, g) that choose to work in occupation j.

Let (q, r) consist of the base worker type (b, ℓ), and let j be given by non-market occupation $j = 0$. Then, we have that $w_{b\ell}^{0} = w_{ig}^{0}$ given the linearity of the production technology of the non-market occupation. Moreover, we have that $\tau_{g}^{0} = \tau_{\ell}^{0} = 0$, $\kappa_{ig}^{0} = \kappa_{b\ell}^{0} = 0$, and $z_{b\ell} = 1$ given our normalizations. Then, we have that:

$$z_{ig} = \left(\frac{\text{Fraction out of labor force}_{ig}}{\text{Fraction out of labor force}_{b\ell}}\right)^{\frac{1}{\eta}} \frac{\text{Avg. market earnings}_{ig}}{\text{Avg. market earnings}_{b\ell}},$$

where Fraction out of labor force$_{ig}$ denotes the share of individuals of type i and subtype g that work in the non-market occupation. Then, we have that workers' productivity is identified from differences in average market earnings and labor force participation relative to the base worker group. In particular, the model implies that workers are estimated to be more productive than the base worker group if their average market earnings are larger, or if they are more likely to be out of the labor force.

To understand the channels underlying these relations, consider an economy with one type-subtype of native and one type-subtype of immigrant whose parameters (preferences, wedges, etc.) are identical except for worker productivity z. Absent this difference, both types of workers would have the same share of individuals out of the labor force, and the same average market earnings. But if workers differ in their productivity z, the workers with higher productivity are endowed with more effective units of labor to supply to the market, leading them to obtain higher average market earnings. In equilibrium, the higher labor supply of this worker type-subtype reduces its market wages relative to the wages in the non-market occupation, leading workers of this type-subtype to be more likely to be out of the labor force. Quantitatively, the former effect dominates the latter general equilibrium effect, implying that average market earnings are critical to identify worker productivity.

Compensation wedges Consider individual type-subtype pairs (i, g) and (q, r), along with some occupation j. The solution of the model implies that:

$$\frac{1-\tau_g^j-\kappa_{ig}^j}{1-\tau_r^j-\kappa_{qr}^j}=\left(\frac{p_{ig,j}}{p_{qr,j}}\right)^{\frac{1}{\eta}}\frac{\text{Earnings}_{ig,j}/z_{ig}}{\text{Earnings}_{qr,j}/z_{qr}}\left(\frac{\sum_{k\in\mathcal{I}(i)}\sum_{v=1}^{G}N_{kv}z_{kv}(p_{kv,j})^{\frac{\eta-1}{\eta}}}{\sum_{k\in\mathcal{I}(q)}\sum_{v=1}^{G}N_{kv}z_{kv}(p_{kv,j})^{\frac{\eta-1}{\eta}}}\right)^{\frac{1}{\sigma_j}}.$$

where the inner summation operator is over all subtypes v of the given worker type, and $\mathcal{I}(t)$ denotes the set of types with the same immigration status (i.e., native or immigrant) as type t.

We back out compensation wedges $\{\tau_g^j\}$ by focusing on native individuals. Consider native individuals ($i = 1$) of subtypes g and r, where we set $r = \ell$ to be given by the base worker subtype. Then, we have that $\tau_\ell^j = 0$ and $z_{1,\ell} = 1$ given our normalizations. Then, the expression above becomes:

$$1-\tau_g^j=\left(\frac{p_{1g,j}}{p_{1\ell,j}}\right)^{\frac{1}{\eta}}\frac{\text{Earnings}_{1g,j}/\text{Earnings}_{1\ell,j}}{z_{1g}/z_{1\ell}}.$$

Note that all the objects in this expression can either be computed directly from the data (such as earnings or the allocation of individuals across occupations $p_{ig,j}\ \forall i, g, j$), or indirectly using data along with the derivations above.

This expression implies that the common compensation wedges τ that apply to all types of natives and immigrants in an occupation j are identified from data on both earnings and participation of natives relative to the base worker type-subtype in such occupation. In particular, natives of subtype g whose earnings in occupation j relative to the base worker type-subtype are lower than their respective relative productivity between them are inferred to be subject to positive compensation wedges τ. Similarly, positive compensation wedges τ are also inferred if natives of subtype g are less likely to choose occupation j than the base worker type-subtype.

We now proceed to back out immigrant compensation wedges $\{\kappa_{ig}^j\}$. Let (i, g) denote an immigrant of this given type and subtype, and let (q, r) consist of the base worker type-subtype (b, ℓ). Then, we have that $\tau_{b\ell}^j = 0$ and $z_{b\ell} = 1$ given our normalizations. Moreover, given that we define natives to be the base individual type ($b = 1$), we additionally have that $\kappa_{b\ell}^j = 0$. Then, the expression above becomes:

$$1-\tau_g^j-\kappa_{ig}^j=\left(\frac{p_{ig,j}}{p_{b\ell,j}}\right)^{\frac{1}{\eta}}\frac{\text{Earnings}_{ig,j}/\text{Earnings}_{b\ell,j}}{z_{ig}/z_{b\ell}}\left(\frac{\sum_{k=2}^{I}\sum_{v=1}^{G}N_{kv}z_{kv}(p_{kv,j})^{\frac{\eta-1}{\eta}}}{\sum_{v=1}^{G}N_{1v}z_{1v}(p_{1v,j})^{\frac{\eta-1}{\eta}}}\right)^{\frac{1}{\sigma_j}}.$$

Note that all the objects in this expression can either be computed directly from the data (such as earnings or the allocation of individuals across occupations $p_{ig,j}\ \forall i, g, j$), or indirectly using data along with the derivations above.

This expression implies that immigrant compensation wedges are identified by relying on similar information as the common compensation wedges. In particular, the expression shows that, conditional on the common compensation wedges τ, any excess under-participation or under-compensation of immigrants in occupation j beyond what is faced by their native counterparts of the same subtype g is interpreted as immigrant compensation wedges.

Additionally, the third term of the right-hand side arises from the imperfect substitutability between natives and immigrants. 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 yet are observed to be equally likely as natives to choose occupation j while being paid as much as natives in such occupation (relative to productivity), then immigrant wedges κ are estimated to be positive. For such immigrant compensation wedges to be zero, the model implies that immigrants would need to be paid relatively more than natives given their relative scarcity. Our findings are robust in economies in which this channel is absent, such as in an economy in which all worker type-subtypes are perfect substitutes.

Occupation productivity Consider an individual of type and subtype (i,g), along with two alternative occupations j and k. Let k be given by the first occupation, such that $k=1$. Moreover, let $\{\sigma_j\}$ be all equal to some value Φ. The solution of the model implies that:

$$A_j = \left\{ \frac{\sum_{v=1}^{G} N_{iv} z_{iv} (p_{iv,j})^{\frac{\eta-1}{\eta}}}{\sum_{v=1}^{G} N_{iv} z_{iv} (p_{iv,1})^{\frac{\eta-1}{\eta}}} \left[\left(\frac{p_{ig,j}}{p_{ig,k}} \right)^{\frac{1}{\eta}} \frac{z_{ig}\left(1-\tau_g^1-\kappa_{ig}^1\right)}{z_{ig}\left(1-\tau_g^j-\kappa_{ig}^j\right)} \frac{(1+\gamma_{ig}^1)\nu_g^1}{(1+\gamma_{ig}^j)\nu_g^j} \right]^{\Phi} \right\}^{\frac{1}{\Phi-1}}.$$

Note that all the objects in this expression can either be computed directly from the data or indirectly using data along with the derivations above.

This expression contrasts the relative labor supply between occupation j and the base occupation ($j=1$) within a given individual type and subtype (i,g). Controlling for differences in wedges and preferences across these occupations, occupations with relatively higher labor supply than the base occupation are inferred to feature higher occupational productivity.

3.4 Implementation

We estimate the parameters of the model following the approach described in the previous subsection. Recall that these derivations are based on the restriction that there is perfect substitution across workers in the inner nest. Thus, we estimate the parameters under this restriction, and solve the model with $\widetilde{\sigma}_j = 100 \ \forall j = 1,...,J$ to approximate an economy with perfect substitution across worker subtypes.

To estimate the model, we restrict attention to individual type and subtypes with at least one observation in a market occupation and at least one observation in the non-market occupation.

Individual type and subtypes without observations in some given occupation are considered under the following imputation: the share of such individuals in the missing occupation is assumed to be infinitesimal, and their earnings in such occupation is assumed to be the average earnings across all observed market occupations for such type-subtype. Our findings are robust to alternative ways to handling missing observations.

4 Immigrant Barriers: Estimates and Impact

In this section we study the extent and implications of immigrant barriers in the U.S. We begin by quantifying the extent to which immigrants are subject to barriers that distort their labor market outcomes relative to their native counterparts. We then investigate the aggregate and distributional implications of immigrant barriers. In Section 5 we study the implications of our findings for immigration policy, and in Section 6 we contrast our findings with those for other countries.

4.1 Estimates of immigrant barriers and productivity

We begin by presenting our estimates of immigrant barriers and productivity in the U.S. These result from the estimation approach described in the previous section. Given the large number of parameters of our model (4558 parameters, as described in Table 2), we restrict attention to reporting summary statistics on the estimated parameters for natives as well as across various types of immigrants based on time since immigration, English proficiency, and country of origin. Specifically, Table 6 reports weighted averages of immigrant compensation wedges $\{\kappa_{ig}^j\}$, immigrant labor supply wedges γ_{ig}^j, and worker productivity z_{ig}. While we focus our discussion on immigrant wedges and worker productivity, we also report estimates of common compensation wedges $\{\tau_g^j\}$, preferences ν_g^j, and occupation productivity A_j. The implications of the model for the distribution of individuals across occupations and their associated earnings are summarized in Table A2, which shows the model-counterparts of the empirical moments presented in Table 1.[8]

Overall immigrant barriers and productivity We find that immigrants in the U.S. are subject to significant immigrant barriers that vary systematically across occupations. The top panel of the table shows that immigrants are subject to severe immigrant compensation wedges to work in cognitive occupations (ranging from 37% to 54% across immigrant subsets), facing substantially lower barriers to work in manual occupations (ranging from 2% to 27% across immigrant subsets). From the lens of the model, these immigrant barriers are likely to distort their labor market outcomes along two dimensions. First, higher average levels of immigrant barriers induce immigrants to stay of the labor force. Second, differences in immigrant barriers

[8]The close match between the moments implied by the model and the data provides support for the accuracy of our approximation of perfect substitution to aggregate workers within the inner nest.

across occupations distort the allocation of immigrants across these.

In contrast to these findings, the middle panel of the table shows that immigrant labor supply wedges are estimated to feature lower dispersion across occupations and immigrant subsets than immigrant compensation wedges. On average, immigrants labor supply wedges are estimated to be positive in routine occupations and negative in non-routine occupations.

Finally, we observe that immigrants are additionally estimated to generally be less productive than natives. With the exception of immigrants in non-routine cognitive occupations, the average worker productivity of immigrants in all other occupations is lower than their native counterparts. This finding shows that immigrant labor market under-performance is jointly accounted by differences in fundamentals between natives and immigrants, as well as by immigrant barriers that distort their occupational choices.

Immigrant barriers and productivity across immigrant types We now examine the extent to which the estimated immigrant barriers differ across immigrant types. Investigating the estimated heterogeneity in immigrant barriers can shed light on the mechanisms underlying them, while also serving to externally validate the reasonableness of our estimates.

We find that there are systematic differences in immigrant barriers and worker productivity across immigrants that differ in the time since immigration. Immigrant compensation wedges are systematically larger across all occupations for immigrants that have lived less than 10 years in the U.S., and their worker productivity is uniformly lower across occupations relative to established immigrant with more than 10 years since immigration. This pattern is intuitive and consistent with previous studies, which point to the time it takes new immigrants to integrate both from the perspective of learning to sidestep any immigrant-specific barriers that might be faced as well as in terms of their effective productivity in the host country.

We also find that there are systematic differences in immigrant barriers and worker productivity by English proficiency and the level of economic development of their country of origin. Compensation wedges in cognitive occupations are higher among immigrants with low English proficiency but largely independent of English skills in manual occupations. In contrast, compensation wedges are estimated to be higher in manual occupations across immigrants from developed countries than those faced by immigrants from less developed countries. The link between worker productivity and these immigrant subsets does not depend on the types of occupations: worker productivity is estimated to be higher among immigrants with high English proficiency and from developed economies.

4.2 Aggregate implications of immigrant barriers

We now investigate the aggregate implications of the estimated immigrant barriers. Our goal is to study how immigrant barriers affect aggregate outcomes such as real GDP, TFP, and employment in the U.S. To do so, we contrast the outcomes implied by the estimated model

Table 6: Estimation results

Occupation Type	Immigrant compensation wedge κ							Common
	N	I_{0-10}	I_{10+}	$\mathrm{I}_{\text{Low Eng}}$	$\mathrm{I}_{\text{High Eng}}$	I_{LIC}	I_{HIC}	comp. wedge τ
Non-routine, Cognitive	0	0.54	0.39	0.47	0.43	0.44	0.45	-0.41
Non-routine, Manual	0	0.04	0.03	0.02	0.08	0.06	0.27	0.09
Routine, Cognitive	0	0.48	0.37	0.53	0.39	0.43	0.42	-0.11
Routine, Manual	0	0.11	0.06	0.05	0.11	0.15	0.22	0.15
Home	0	0	0	0	0	0	0	0
	Immigrant labor supply wedge γ							Common
Occupation Type	N	I_{0-10}	I_{10+}	$\mathrm{I}_{\text{Low Eng}}$	$\mathrm{I}_{\text{High Eng}}$	I_{LIC}	I_{HIC}	pref. ν_g^j
Non-routine, Cognitive	0	-0.04	-0.03	-0.14	-0.03	-0.03	-0.01	0.44
Non-routine, Manual	0	-0.06	-0.07	-0.14	-0.01	-0.04	0.15	0.70
Routine, Cognitive	0	0.09	0.00	-0.05	0.03	0.09	0.07	0.55
Routine, Manual	0	0.02	-0.02	-0.06	0.02	0.03	0.13	0.54
Home	0	0	0	0	0	0	0	1.00
	Worker productivity z							Occupation
Occupation Type	N	I_{0-10}	I_{10+}	$\mathrm{I}_{\text{Low Eng}}$	$\mathrm{I}_{\text{High Eng}}$	I_{LIC}	I_{HIC}	prod. A
Non-routine, Cognitive	1.50	1.62	1.75	0.92	1.74	1.78	2.01	1.00
Non-routine, Manual	1.18	0.88	1.01	0.73	1.09	1.05	1.41	0.40
Routine, Cognitive	1.23	1.14	1.21	0.77	1.26	1.26	1.60	0.54
Routine, Manual	1.26	0.90	1.01	0.75	1.10	1.08	1.51	0.87
Home	1.21	1.10	1.12	0.73	1.27	1.25	1.57	0.40

Note: This table presents estimated common compensation wedges τ, immigrant compensation wedges κ, preference shifter ν, immigrant labor supply wedges γ, worker productivity z, and occupation productivity A. Estimated outcomes are obtained for each worker type/subtype and each occupation. For expositional purposes, aggregated moments are reported for natives and immigrant types across all occupations. The base group of prime-age, male, non-college natives face no compensation wedges to work in any of the market occupations. Worker productivity z is expressed as a multiple of values for a base subtype (young, male, non-college natives. N denotes natives, I_{0-10} denotes recent immigrants ($\leq$ 10 years), I_{10+} denotes established immigrants (>10 years), $\mathrm{I}_{\text{Low Eng}}$ denotes low English proficiency immigrants, $\mathrm{I}_{\text{High Eng}}$ denotes high English proficiency immigrants, I_{LIC} denotes immigrants originating from low income countries, and I_{HIC} denotes immigrants originating from high income countries.

with those implied by a counter-factual economy in which immigrant wedges are removed. In particular, we consider a counter-factual economy with immigrant wedges given by $\{\widetilde{\gamma}_{ig}^j\}$ and $\{\widetilde{\kappa}_{ig}^j\}$, where we set $\widetilde{\gamma}_{ig}^j = \min\{\gamma_{ig}^j, 0\}$ and $\widetilde{\kappa}_{ig}^j = \min\{\kappa_{ig}^j, 0\}$. That is, we set positive immigrant wedges to zero and we keep negative immigrant wedges unchanged at their estimated values.[9]

Table 7 presents the effects of removing immigrant wedges on output, productivity, and employment both in the aggregate and across occupations. We find that removing the barriers faced by immigrants in U.S. labor markets increases real GDP by 2.63 percent. This output increase is driven by two channels: (*i*) an inflow of immigrants from being out of the labor force into market occupations, and (*ii*) the reallocation of workers across market occupations.

[9]Our findings are robust to setting all immigrant wedges to zero.

Table 7: Aggregate and sectoral effects of removing wedges

Occupation Type	Percent change Real GDP	TFP	Labor	Change in immigrant share (pp)
Aggregate	2.63	-0.24	2.88	3.27
Non-routine, Cognitive	3.31	-1.23	4.60	4.56
Non-routine, Manual	-1.48	4.06	-5.32	-3.04
Routine, Cognitive	7.30	-2.91	10.51	9.29
Routine, Manual	-0.33	2.05	-2.33	-0.77

Note: This table presents the percent change in aggregate and occupation-specific real GDP, TFP, and labor when immigrant wedges are set equal to their counterpart natives of the same subtype. A reference worker type (prime-age, male, non-college natives) have wedges set to zero. Aggregate real GDP is output produced in the market sector; total factor productivity (TFP) is real GDP per worker, and labor is the mass of workers in the market sector (or each occupation). The change in immigrant share denotes percentage point change in the fraction of immigrants employed in the market sector or each occupation.

As a result, the increase of total employment is accompanied by a small decline of total factor productivity (TFP). This decline of TFP is a byproduct of two opposing forces. On the one hand, market occupations experience an inflow of less-productive workers who switch from non-market to market occupations, leading to lower average productivity, especially in occupations that absorb a large mass of such switchers. On the other hand, improvements in the allocation of workers across market occupations leads to an increase in average productivity.

We find significant heterogeneity in the effects of removing immigrant wedges across occupations. Output in cognitive occupations increases significantly (3.31% in non-routine cognitive, and 7.30% in routine cognitive), while declining in manual occupations (-1.48% in non-routine manual, and -0.33% in routine manual). This pattern mirrors the distribution of immigrant wedges across occupations documented in the previous subsection: immigrant compensation wedges are significantly larger in cognitive occupations relative to manual occupations.

In tandem with these heterogeneous effects, we find that the sources of these output changes vary significantly across occupations. Manual occupations feature a significant outflow of workers, which increases productivity as the workers with the lowest productivity in such occupations are those who leave. In contrast, cognitive occupations observe a large inflow of workers both from non-market occupations as well as from manual occupations. These workers have lower productivity in these occupations than those who were already choosing them, reducing average productivity — prior to the policy change, the productivity of the former was not sufficiently high to overcome immigrant barriers.

Quantitative significance We now evaluate the quantitative significance of our findings. To do so, 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

Table 8: Quantitative importance of wedges relative to immigrant labor supply

	Real GDP	TFP	Labor
No immigrants	0.70	0.89	0.79
Baseline	1.00	1.00	1.00
No immigrant wedges	1.03	1.00	1.03
Gains ratio	6.18		

Note: This table presents a comparison of real GDP, total factor productivity (TFP), and labor under three scenarios: (1) when all immigrants are removed from the economy, (2) the baseline economy, and (3) when wedges faced by immigrants in excess of those that natives face are removed.

substantial. Thus, we now 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 8 reports the value of real GDP, TFP, and employment relative to the baseline for three economies: the economy without immigrants, the baseline, and the economy without immigrant wedges examined above. We find that the real GDP gains from immigration are equal to 42.5% relative to an economy without immigrants ($1.00/0.702 \times 100$). This implies that the real GDP gains from removing immigrant wedges are approximately 6.18% of the total gains from immigration ($2.63/42.5 \times 100$). We conclude that removing immigrant wedges significantly increases the overall contribution of immigrants to the U.S. economy. In particular, their current contribution to the U.S. economy would increase by 6.18% in the absence of immigrant barriers.

4.3 Distributional implications of immigrant barriers

The aggregate effects reported in the previous subsection result from removing the barriers faced by all immigrants in the U.S. economy, regardless of their individual observable characteristics. But, as we reported in Section 4.1, immigrant barriers differ substantially across occupations and immigrant types, such as by time since immigration, English proficiency, or country of origin. Similarly, immigrant barriers also differ substantially across demographics, as captured by immigrant subtypes, such as age, gender, or education.

In this section we investigate the distributional implications of immigrant barriers. To do so, we investigate the relative impact of removing immigrant wedges across immigrants with alternative observable characteristics. We begin by contrasting the impact of removing immigrant wedges across alternative immigrant types and subtypes, and then investigate the impact of removing immigrant wedges across specific occupations. These exercises allow us to shed light on the types of immigrants that experience the largest labor market distortions as we as on the heterogeneous payoffs associated with the targeted removal of immigrant wedges.

4.3.1 Heterogeneous effects across immigrant types and subtypes

We study the impact of immigrant wedges across alternative immigrant types and subtypes by removing immigrant wedges across subsets of the immigrant population. To do so, we compute the impact of removing only the immigrant wedges faced by immigrants of some given type i or subtype g, comparing the baseline model with a counter-factual economy identical to the baseline except that immigrant wedges across immigrants of the given type or subtype are set to zero.[10,11]

Our findings are reported in Table 9. The first column of the table shows the real GDP gains implied from separately removing the wedges faced by each immigrant group listed in the rows of the table. Given that the number of immigrants differs across the alternative immigrant groups that we study, the third column reports the real GDP gains from removing immigrant wedges controlling for these differences. Specifically, we use the share of immigrants that belong to each group (the second column) to express the real GDP gains per 1% of immigrants in the total population.[12]

We find that there are significant differences in the effects from removing immigrant wedges across the various demographic groups, particularly by gender and education. For instance, the real GDP gains per immigrant from removing the immigrant wedges faced by females are more than twice as large as those for males. Removing immigrant wedges faced by women increases real GDP by 0.18% per percentage point of the population that is a female immigrant, while the respective value for men is 0.08%. The removal of wedges for female immigrants result in a larger outflow from the home sector and a larger degree of reallocation within the market sector towards cognitive occupations. These larger effects are accounted by the higher immigrant wedges faced by female immigrants relative to their male counterparts.

Similarly, larger real GDP gains are also observed across college graduates. These gains are the largest for immigrants with STEM-related degrees, followed by immigrants with degrees in social sciences. For STEM graduates, these gains are driven by a large outflow of STEM graduates from the home sector towards the market sector. All market sectors experience an increase in their immigrant shares, with larger inflows into routine cognitive and non-routine manual occupations. For Social Science graduates, we also observe a large outflow from the home sector but a key difference is that reallocation within the market sectors is substantial. Similar patterns are observed of Law or Medical graduates.

We also find significant heterogeneity in the effects from removing immigrant wedges across

[10] For instance, to compute the impact of removing immigrant wedges on new immigrants, we compare the baseline with a counter-factual identical to the baseline except that the immigrant wedges faced by new immigrants are set to zero.

[11] As in the previous section, we only set positive immigrant wedges to zero, keeping negative immigrant wedges at their baseline values. Our findings are robust to setting all immigrant wedges to zero.

[12] Column 3 is derived by dividing column 1 by column 2 and multiplying by 0.01.

Table 9: Gains from removing wedges by immigrant type/subtype

Category	Immigrant Type/Subtype	Real GDP (% Δ)	Share of labor force (baseline level, %)	Real GDP growth per 1% of imm. (%)
Age	Young	0.79	5.58	0.14
	Prime-age	0.91	6.99	0.13
	Old	0.77	6.45	0.12
Sex	Male	0.72	9.09	0.08
	Female	1.81	9.93	0.18
Education	Non-college	1.34	12.02	0.11
	STEM	0.54	3.08	0.18
	Law or Medical	0.07	0.61	0.12
	Social Sciences	0.52	3.32	0.16
Duration	Immigrants	2.63	19.02	0.14
	New immigrants	0.94	5.53	0.17
	Old immigrants	1.58	13.49	0.12
Country of origin	High-income country	0.42	2.44	0.17
	Middle-income country	1.25	10.86	0.12
	Low-income country	0.80	5.72	0.14
English proficiency	No English	0.20	1.26	0.16
	Some English	0.43	3.23	0.13
	Fluent English	1.93	14.53	0.13

Note: This table presents the effect of removing wedges faced by immigrants (relative to natives) on real GDP. In the last column of the table, we adjust for the size of each immigrant type by presenting the ratio of real GDP growth to the share of each immigrant type/subtype in the labor force.

immigrant groups. Recent immigrants and immigrants with the lowest English proficiency experience the largest real GDP gains per immigrant. While these findings suggest that newcomers face significant frictions in the labor market, the smaller real GDP gains from removing the immigrant wedges of established immigrants and those with strong English proficiency suggest that these frictions are not persistent and decay over time.

4.3.2 Heterogeneous effects across occupations

Finally, we investigate the degree of heterogeneity from removing immigrant wedges across occupations. To do so, for each occupation j at a time, we examine the impact of removing the immigrant wedges faced by all immigrants to work in such occupation.[13] Table 10 presents the effects on real GDP for each occupation.

We find that, when immigrant wedges in a given occupation are removed, immigrants from

[13] As in the previous sections, we only set positive immigrant wedges to zero, keeping negative immigrant wedges at their baseline values. Our findings are robust to setting all immigrant wedges to zero.

Table 10: Gains from removing immigrant wedges by occupation

Occupation	Real GDP	Share of labor force	Real GDP growth
	(% Δ)	(baseline level, %)	per 1% of imm. (%)
Non-routine, Cognitive	1.23	5.38	0.23
Non-routine, Manual	0.12	2.75	0.04
Routine, Cognitive	0.53	2.01	0.26
Routine, Manual	0.86	3.64	0.24

Note: This table presents the effect of removing wedges faced by immigrants (relative to natives) on real GDP and share in labor force by occupation type. In the last column, we adjust for the relative size of immigrants in each occupation by presenting the ratio of real GDP growth to the share of each immigrant type in the occupation.

other occupations (or the non-market occupation) are diverted towards this occupation. This implies that removing wedges to work in low-productivity occupations results in smaller increases of aggregate output, while the opposite is true for high-productivity occupations. This finding reveals that while simultaneously removing all immigrant wedges is output-enhancing in the aggregate, removing immigrant wedges across a subset of the occupations is not always desirable from the perspective of aggregate output.

These differences are significantly muted when examining the real GDP gains per immigrant, with the exception of non-routine manual occupations where the real GDP gains are much smaller than the other occupations in both absolute terms and per immigrant. These findings suggest that immigrants are significantly more likely to choose to work in productive occupations, offsetting the broad differences in the overall GDP gains when expressing these per immigrant.

5 Immigration Policy Reform

We now investigate various implications of the aggregate and distributional effects of immigrant misallocation documented in the previous section. In this section we study the implications for immigration policy, while in the following section we investigate the extent and effects of immigrant misallocation across countries.

The findings reported in the previous section focus on the effects of reallocating the stock of immigrants currently living in the U.S. across occupations to overcome any immigrant-specific barriers they might be subject to in U.S. labor markets. Thus, the stock of immigrants is taken as given throughout the analysis. We now investigate the implications of immigrant barriers for changes 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 the output per worker gains from admitting new immigrants into the U.S. differ across immigrant types? Second, how are these returns to increased immigration affected by the immigrant wedges that new immigrants might be subject to upon arrival? We interpret the answers to these questions as informative about the potential effects of implementing alternative immigration policies in the U.S.

Importantly, note that the output and productivity effects of increased immigration fundamentally depend on how new immigrants affect the allocations and earnings of natives and previous immigrants. Thus, before evaluating alternative immigration policies, in Section 5.1 we contrast the model's implications for the labor outcomes of natives and previous immigrants following an increase in the stock of immigrants vis-a-vis their empirical counterpart. Critically, we use the model to compute elasticities which are comparable to empirical estimates obtained from influential microeconomic studies. This validation exercise allows us to verify that the magnitudes of key elasticities in our model align well with their empirical counterparts. Next, in Section 5.2, we use our model to answer the aforementioned questions on the effects of alternative immigration policies.

5.1 Microeconomic elasticities: model vs data

To contrast various key microeconomic elasticities implied by our model with previous estimates from the literature, we begin by discussing the set of empirical studies that we focus on. We then proceed to construct a counter-factual experiment to serve as the model-counterpart of these empirical studies. We conclude this subsection by contrasting the implications of our model with the empirical estimates from the literature.

Empirical estimates Empirical studies on the labor market effects of immigration have relied on a variety of alternative approaches. Dustmann, Schönberg, and Stuhler (2016) classify these studies into three groups. The first is the national skill-cell approach, which categorizes immigrants and natives into education-experience cells (skill cells) and exploits national-level variation in skill-cell-specific inflows of immigrants. The second is the pure spatial approach, which uses variation in the inflow of immigrants across regions. Finally, the third is a mix of the skill-cell and pure spatial approaches, studying variation in the inflow of immigrants both across skill groups and across regions.

Dustmann, Schönberg, and Stuhler (2016) argue that the estimates from these alternative approaches are not directly comparable and that only the pure spatial approach identifies the total effect of immigration on labor market outcomes of a particular skill group, while the other two identify the relative effect of immigration by education or experience. Thus, analyzing the total effects through a pure spatial approach provides easily interpretable estimates that are policy relevant. We therefore focus on empirical estimates of the effects of immigration based on the spatial approach.[14]

[14] In addition, this methodology does not rely on the pre-classification of individuals into skill cells, which requires that the education and experience of immigrants and natives be comparable. Dustmann, Schönberg, and Stuhler (2016) illustrate that immigrants typically downgrade their education and experience upon arrival to the U.S., the U.K, and Germany. Thus, assuming that immigrants of a given education and experience type are directly comparable to their native counterparts may lead to misclassification and affect the magnitude of

Table 1 in Dustmann, Schönberg, and Stuhler (2016) describes a variety of papers that implement the spatial approach using data from different time periods and countries. To keep this section focused but at the same time relevant, we turn to papers that analyze the effects of a widely-studied and large-scale immigration shock experienced in the U.S. in 1980. Specifically, between May and September 1980, around $125,000$ Cuban immigrants (the *Marielitos*) arrived in Miami after Fidel Castro declared that Cubans wishing to immigrate to the U.S. were free to leave Cuba from the port of Mariel. Several papers (see, for example, Card 1990; Borjas 2017; and Peri and Yasenov 2017 among others) measure elasticities of labor market outcomes to an immigration shock by comparing outcomes in Miami and control cities before and after the arrival of the Marielitos to Miami (the "Marielitos shock"). Importantly, these studies provide key elasticities not only for the aggregate population but also across subpopulations, serving a useful empirical counterpart for us to contrast the implications of our model.

The Marielitos increased the labor force of Miami by around 8 percent. They were more likely to be young, male, and with less education: only 18 percent of the Marielitos had a college degree, 56 percent of them was male, and 39 percent was younger than age 30. Empirical studies used this sudden inflow of immigrants to Miami 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: Atlanta, Los Angeles, Houston, and Tampa-St. Petersburg. This study concludes that the inflow of immigrants had *no* impact on the labor market outcomes of natives and previous immigrants in Miami.

Two particularly important related studies, among many others, are Borjas (2017) and Peri and Yasenov (2017). Borjas (2017) argues that measuring the effects of immigrants requires carefully matching the skills of immigrants with those of the pre-existing labor force. He also disagrees with the choice of control group, i.e. comparison cities, in Card (1990) because Card (1990) chooses comparison cities based on trends observed after the immigration shock rather than prior to the treatment. Benefiting from the developments in empirical research over time, Borjas (2017) implements the synthetic control method to create a new synthetic city that best resembles the pre-Marielitos labor market in Miami.[15] He concludes that, once the skills of immigrants are matched with those of the existing workforce and the control city is created based on the pre-treatment labor market outcomes, the wages of high school dropouts in Miami declined significantly after the inflow of the Mariel immigrants.

empirical estimates.

[15]In particular, the synthetic control method estimates weights for each existing city so that the resulting synthetic control city looks very similar to the treated city in terms of the labor market moments taken into account while searching for city weights. For example, Borjas (2017) matches the pre-immigration labor markets of Miami and the synthetic city based on the rate of employment growth in the 4-year period prior to the Marielitos shock and the concurrent rate of growth of employment and wages among high school dropouts.

However, Peri and Yasenov (2017) argues that the results in Borjas (2017) hold only in small sub-groups when using the March-CPS instead of ORG-CPS.[16] In particular, Peri and Yasenov (2017) show that small subpopulations of the March-CPS exhibit significant fluctuations in their average weekly wages in Miami around the long-run trend between 1972 and 1991. Further, these negative or positive fluctuations are no different after the Marielitos shock. Meanwhile, the larger samples of the ORG-CPS experience only small fluctuations around the trend and exhibit no significant change in wages after 1979. In addition, they also emphasize that it is important to consider a longer pre-1979 period to match the labor market outcomes between Miami and the control city given the small sample size before 1979 in the data. Overall, after using the synthetic control method to generate the control city which resembles Miami's labor market based on a longer pre-treatment period and accounting for large measurement errors for small samples in the data, Peri and Yasenov (2017) confirm the early findings of Card (1990) as they also find that wages and unemployment rates of high school dropouts did not change significantly between Miami and the control group after the immigration shock.

Model-counterpart to empirical estimates We contrast the implications of the model with the effects of the Marielitos shock documented by Card (1990). To do so, we construct a model-counterpart to this shock, considering a counterfactual in which new immigrants with similar characteristics as the Marielitos become part of the U.S. economy. We use our model of the U.S. economy as our model of Miami upon the arrival of the Marielitos. Thus, we increase the total mass of new immigrants such that the total population increases by 8 percent. In order to match the demographics of the Marielitos, we assume that all new immigrants in the counterfactual originate from middle-income countries, given that Cuba was a middle-income country based on our classification in Section 3.1. Furthermore, we let 82 percent of the new immigrants have no college degree, while we let 18 percent have college degrees; 55.6 percent are male and 44.4 percent to be female; and 38.7 are classified under the first age group (25-34) and the rest equally divided across the remaining age groups (35-44 and 45-54). This allows us to closely match the education, gender, and age distribution of the Marielitos.[17]

Results We solve the model under the Marielitos shock described above and contrast its implications for wages and unemployment rates with the baseline model estimated to match salient features of the U.S. economy. First, for each economy we compute averages of the logarithm of unit wages w and the unemployment rate (fraction in the home sector) across natives and immigrants. Then, we compute differences in these outcomes between the two economies.

[16] As Peri and Yasenov (2017) note, most papers studying the labor market effects of the Marielitos shock use the ORG-CPS instead of the March-CPS.

[17] We do not have information about 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.

Table 11: Effects of immigrants on labor market outcomes of natives and immigrants

Moment	Data	Model
Change in log wages of natives (pp)	0.5	1.1
Change in log wages of less-educated natives (pp)	1.1	1.1
Change in unemployment rate of natives (pp)	-1.7	-0.8
Change in log wages of immigrants (pp)	-4.5	-4.5

Note: This table compares changes in labor market outcomes of natives and immigrants upon 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 labor market outcomes of natives and immigrants after the arrival of Cuban immigrants to Miami in 1980. Using our model, we simulate the same experiment to obtain model-based estimates.

Table 11 reports changes in key labor market outcomes of natives and immigrants upon the inflow of the Marielitos in both the data and the model.[18] Overall, the empirical estimates show that the inflow of Mariel immigrants had limited effects on the labor market outcomes of natives but much larger effects on the wages of immigrants in Miami.[19] This result is largely consistent with the implications 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 by the imperfect substitutability between immigrant and native labor inputs in the production technologies. Imperfect substitution limits the degree to which the rise in immigrant labor supply crowds out native labor supply. In addition, the rise of immigrant labor supply leads to an increase in production as native labor supply also increases slightly. That is, the fraction of natives outside the market sector, i.e., the native unemployment rate, declines. As reported in the third column of Table 11, an economy that features perfect substitution between immigrants and natives implies strong crowding-out effects of immigrants on natives, leading natives to experience a sizeable decline in wages and a sizable increase in their unemployment rate.

On the other hand, our model implies a more sizable change in the wages of previous immigrants. Two channels account for this implication. First, as described above, the Mariel immigrants were pre-dominantly less-educated. Given that we exactly match the distribution of

[18]We use Table 3 in Card (1990) to calculate the change in the logarithm of real hourly earnings of white natives in Miami relative to that in comparison cities between 1981 and 1982 relative to 1979. Similarly, we use Table 4 in Card (1990) to calculate the change in the unemployment rate of white natives in Miami relative to that in comparison cities between 1981 and 1982 relative to 1979. Table 3 in Peri and Yasenov (2017) provides regression estimates for the change in the logarithm of real hourly earnings for high-school dropouts in Miami relative to the synthetic control city between 1981 and 1982 relative to 1979. Finally, Table 7 in Card (1990) provides differences between the logarithm of real hourly earnings of Cuban immigrants in Miami and rest of the U.S. between 1979 and 1985. We use these values to calculate the change in Cuban immigrant wages in Miami relative to Cuban immigrants in the rest of the U.S. between 1981 and 1982 relative to 1979.

[19]Note that these point estimates can sometimes vary depending on the specification (due to using different measures for earnings or changes in the control city definition) or time horizon given the small number of observations in the data used to estimate these effects. However, in these scenarios, the estimated effects of the inflow of Mariel immigrants on labor market outcomes are small in magnitude for natives and much larger for immigrants, a result that is consistent with our model-based estimates.

demographics among the Mariel immigrants, these new immigrants select into less-productive occupations that pay lower wages, decreasing the average wages of immigrants in the economy. Second, the production technology in our model features perfect substitutability in the labor supply of different types of immigrants. Thus, an increase in the labor supply of immigrants reduces the average wages of immigrants.

5.2 Immigration policy

The previous subsection shows that our model is consistent with empirical estimates of the response of key labor market outcomes to changes in immigrant labor supply. Then, we now use our estimated model to investigate the potential impact of a broad set of alternative changes to U.S. immigration policy. We focus on policies that increase the stock of immigrants that live in the U.S., and examine the relative impact of admitting pools of immigrants with alternative sets of characteristics. Critically, we investigate the extent to which immigrant barriers affect the implied impact of such potential policy changes.

To do so, we consider an inflow of new immigrants which increases the total mass of immigrants in the U.S. economy by 10 percent — that is, from 19.02% to 20.93% of the U.S. population in the 25-54 age group. We compute the implications for real output per worker (TFP) to isolate the impact of increased immigration on productivity relative to its mechanical impact on total output. We contrast alternative approaches to increasing immigration by considering alternative compositions of the pool of new immigrants, as we describe below in more detail. Table 12 reports the effects of these alternative policies on real output per worker in our baseline model, while the second row of the column reports the impact of the same experiment in our baseline economy after the removal of immigrant barriers.

We begin by examining the effects of these policies in the baseline model. The first row of the table reports the effects of increasing immigration as describe above when considering a pool of new immigrants whose distribution across types and subtypes is identical to the current distribution of recent immigrants in the U.S. We find that this policy change increases output per worker by approximately 0.33%. That is, we find that new immigrants not only mechanically increase the stock of potential workers in the economy, but they also increase the effective productivity of the overall stock of U.S. workers. With a different composition across demographics along with skills that are complementary to those of natives, a larger population of immigrants increases overall U.S. productivity.

Interestingly, we find that the impact of increased immigration differs substantially depending on the composition of the pool of new immigrants. Rows 2 to 16 of the table show the effects of increasing immigration when the pool of new immigrants is restricted to be of a particular demographic or immigrant types.[20] For instance, if the U.S. implements an immigration policy

[20]We assume that the distribution of new immigrants across the remaining types and subtypes is as in the

Table 12: Immigration policy: Gains from admitting new immigrants by immigrant type/subtype

Category	Immigrant Type/Subtype	Baseline model	No immigrant wedge model
All		0.33	0.23
Age	Young	0.21	0.11
	Prime-age	0.46	0.44
	Old	0.29	0.25
Sex	Male	0.45	0.61
	Female	0.19	-0.09
Education	Non-college	-0.41	-0.81
	STEM	1.37	1.72
	Law or Medical	0.73	0.79
	Social Sciences	0.75	0.73
Country of origin	High-income country	0.35	0.30
	Middle-income country	-0.04	-0.21
	Low-income country	1.28	1.42
English proficiency	No English	-0.51	-0.78
	Some English	-0.48	-0.71
	Fluent English	0.64	0.73

Note: This table presents percent changes in output per worker (TFP) when we increase the total mass of a certain recent immigrant (type, subtype) such that the total mass of all immigrants in the economy increases by 10 percent. In particular, the first column shows percent changes in output per worker 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). The first row shows the percent change in output per worker when we increase the mass of new immigrants uniformly across all subtypes. The remaining rows show percent changes in output per worker when we increase the mass of new immigrants of a certain subtype of immigrants.

that only admits immigrants with no college degree or immigrants who are not fluent in English, output per worker declines by around 0.5 percent. On the other hand, when the immigration policy favors those with a college degree, output per worker increases significantly ranging from 0.73% for Law or Medical to 1.37% for STEM — the latter is akin to an expansion of the H1B visa policy in the U.S. Additionally, we find that highest output per worker gains are achieved when the immigration policy targets prime-age (35-44) workers, implying that gains exhibit an inverse-U-shaped pattern in age.

The second column of Table 12 shows that the impact of increased immigration depends critically on the extent to which immigrants are subject to immigrant-specific barriers in U.S. labor markets. In particular, we find that the gains from admitting immigrants with a college degree from a STEM field or ones who are fluent in English are amplified when they are brought into an economy with no immigrant-specific distortions. In an economy with no immigrant wedges, the allocations of workers across occupations only depend on their relative productivity

overall U.S. distribution of recent immigrants.

across occupations. Thus, new immigrants allocate to those occupations in which they are most productive, increasing the productivity gains from admitting such immigrants. On the other hand, output per worker declines more in an economy without immigrant wedges compared to our baseline economy when the immigration policy admits more immigrants without a college degree or immigrants who are not fluent in English. With immigrant barriers, these immigrants are more likely to stay out of the labor force given that their low productivity in market occupations. However, without immigrant wedges, a higher fraction of such new immigrants enter market occupations, leading to a higher drop in output per worker.

These findings show that that effects of increased immigration vary greatly depending on the composition of the new immigrant pool. And, critically, that these effects are amplified in the absence of immigrant barriers.

6 Immigrant Misallocation Across Countries

Thus far, we have analyzed the aggregate and distributional implications of barriers faced by immigrants in U.S. labor markets. This analysis raises several questions. To what extent is the U.S. an attractive destination for immigrants? More generally, how different are immigrant barriers and their implications across countries? While an exhaustive comparison of labor market institutions across countries is beyond the scope of the paper, we now address these and other related questions by recomputing the analysis conducted for the U.S. using cross-country data.

Data We use cross-country survey data from the Luxembourg Income Study (LIS) database, which collects information from surveys that are originally conducted typically by national institutions in each respective country. The LIS publishes data in waves which are typically three to five years apart. Currently, the LIS has 11 waves covering between 1980 and 2020. For each country in the LIS database, we restrict attention to data from the most recent survey for which the country has the information necessary to conduct our analysis. This is mostly Waves 10 and 11 which cover the period from 2015 to 2020.[21]

The LIS database contains person-level data on labor income, labor market outcomes (including employment status, occupation, and usual weekly hours worked), demographics (including education, age, and gender), as well as immigration status.[22] Individuals are partitioned into types and subtypes as in the U.S., but with a few exceptions. Given data limitations across most countries, we abstract from differences across immigrants by time since immigration, fluency in the language of the host country, and income level of the country of origin. Additionally, we maximize comparability across countries by considering two education categories, i.e., non-

[21]We also do not use any data from 2020 to exclude potential effects from the COVID-19 pandemic.

[22]Labor income in each country is provided in the country's local currency. We use the purchasing power parity (PPP) and consumer price index (CPI) data provided by LIS to convert labor income amounts over time and across countries to 2019 US dollars.

college vs college. Among the set of countries that provide the necessary information to estimate the model, we focus on those in which the share of immigrants among the employed population is at least 2 percent. As in the ACS, we restrict our sample to non-business owner individuals between the ages of 25 and 54 who are not on active military duty. Our final sample consists of 19 countries with homogenized target moments on the distribution of individuals and annual income across demographics and occupations.

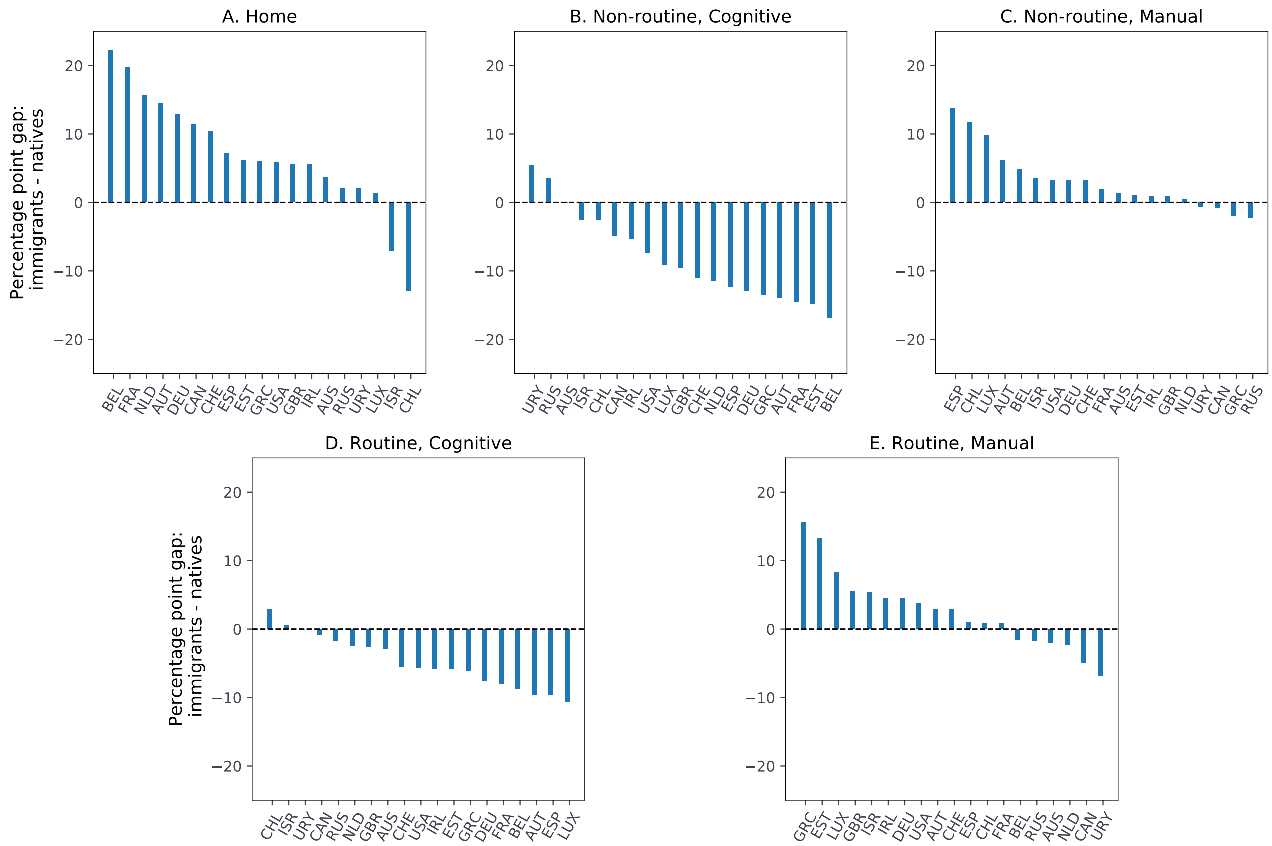
The LIS database provides information on the current occupation of employed workers. Occupations for each country in our analysis are based on either the International Standard Classification of Occupations (ISCO) codes or the country's own occupation classification. We map each country's occupation classification into SOC by using crosswalks between ISCO and SOC for countries with ISCO codes, and crosswalks between country-specific occupation codes and ISCO and then between ISCO and SOC for the remaining countries. We then classify each individual's reported occupation into one of the four task-based occupation categories, as we implemented in Section 3.1 using the ACS.[23] Appendix A.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 and their average labor earnings in each occupation since these are the moments used to estimate the parameters of 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 labor earnings in each occupation. Then, for each occupation we compute i) the percentage point gap (calculated as immigrants − natives) between the fraction of immigrants and natives that choose it and ii) the percent gap (calculated as immigrants/natives − 1) between the earnings of immigrants and natives. Figures 1 and 2 plot these two moments across countries in our sample, respectively.

We highlight salient differences across countries in the allocation of immigrants and natives across occupations. First, while the fraction of immigrants out of the labor force is higher than across natives in almost all countries, this gap between immigrants and natives varies significantly across countries. For example, while this gap is 6 percentage points (pp) in the U.S. and the U.K. (GBR), it is 22 pp in Belgium (BEL), 13 pp in Germany (DEU), and 11 pp in Canada (CAN), implying that the incidence of non-employment among immigrants is much larger than that of natives in these countries when compared to the U.S. and the U.K. Second, immigrants are underrepresented in non-routine cognitive occupations (the occupation with the highest average earnings in all countries) and overrepresented in non-routine manual occupations (the occupation with the lowest average earnings in all countries) in almost all countries. Notably,

[23] In addition, some individuals are classified to be in the home sector using the same definition of home sector as in Section 3.1 using the ACS.

Figure 1: Cross-country differences in allocations between immigrants and natives

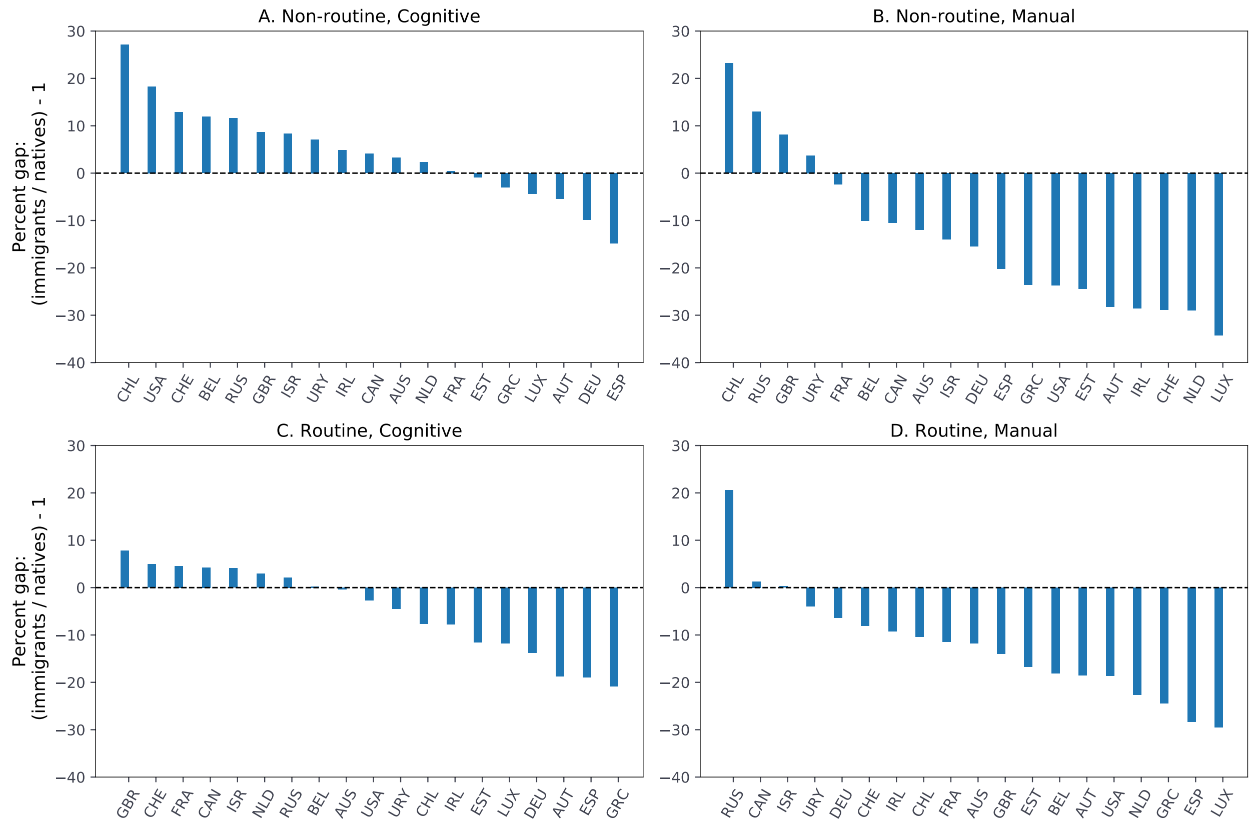


Note: This figure presents differences in labor market allocations between immigrants and natives across countries. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives). The figure shows the percentage point gap (calculated as immigrants − natives) between fractions of immigrants and natives in each occupation across countries. Harmonized data on immigration status, employment, income, and demographics are obtained from the Luxembourg Income Study Database.

there are sizable differences in the gap between the fraction of immigrants and natives in these occupations across countries. For instance, while the fraction of immigrants in non-routine cognitive occupations is 7 pp (13 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 close to each other in the U.S. and the U.K., immigrants are overrepresented in these occupations in Spain (ESP) and Chile (CHL).

Moving to the earnings gap between immigrants and natives in each occupation, Figure 2 shows that its magnitude and sign varies significantly across countries and occupations. Interestingly, we find that in two-thirds of the countries in our sample the average earnings of immigrants are larger than natives in non-routine cognitive occupations, exhibiting significant dispersion across countries. For example, the average earnings of immigrants are 18 percent larger than natives in the U.S., but these are 15 and 10 percent lower in Spain and Germany, respectively. On the other hand, the average earnings of immigrants are significantly lower than

Figure 2: Cross-country differences in earnings between immigrants and natives



Note: This figure presents differences in earnings between immigrants and natives across countries. For each country, the average labor earnings of immigrants and natives in each occupation. The figure shows the percent gap (calculated as immigrants/natives − 1) between earnings of immigrants and natives in each occupation across countries. Harmonized data on immigration status, employment, income, and demographics are obtained from the Luxembourg Income Study Database.

natives in non-routine manual occupations across most countries, but the magnitude of this earnings gap exhibits significant heterogeneity: in these occupations, immigrants earn, on average, 24 percent less than natives in the U.S., 15 percent less in Germany, and 11 percent less in Canada.

It is important to note that differences in labor market allocations and earnings between immigrants and natives across countries can be driven by differences in their demographics. Our model accounts for these demographic differences between immigrants and natives given that it explicitly partitions individuals along various demographic groups such as gender, education, and age. In Appendix A, Figures A1, A2, and A3 document how allocations and earnings gaps between immigrants and natives differ across countries along various gender, education, and age groups, respectively. These considerations 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 barriers across countries: Estimates and aggregate effects The evidence above shows that differences in the labor market outcomes between immigrants and natives vary substantially across countries. We now investigate the extent to which these differences reflect differences in immigrant barriers across countries or whether they are accounted by cross-country differences in fundamentals such as productivity or preferences. To do so, we separately estimate the model for each country in our sample, following the approach described in Section 3. In particular, we target the same distributional and labor income moments summarized in Figures 1 and 2. Then, for each country, we compute the effects of removing immigrant wedges as in Section 4, by setting all immigrant wedges to zero, and comparing the implied outcomes with those of the estimated model.

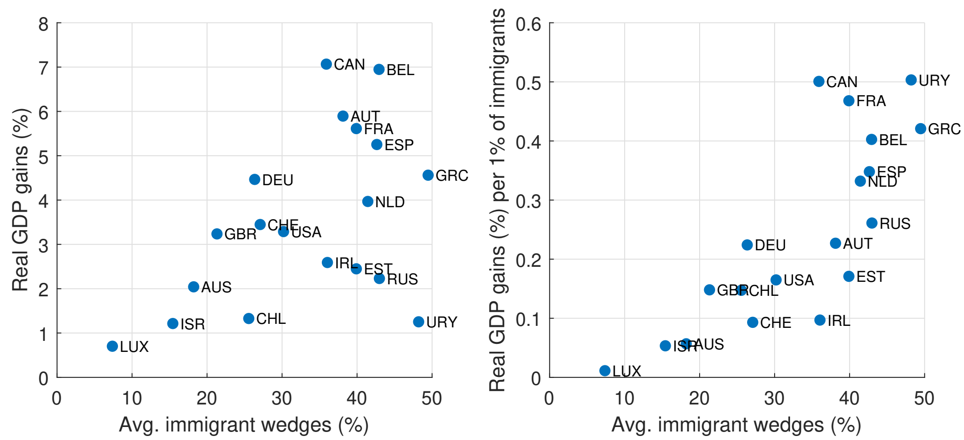
The left panel of Figure 3 presents the relation between the estimated average immigrant compensation wedges across countries (x-axis) and the real GDP gains from removing them (y-axis).[24] We find that there is a large degree of dispersion in immigrant barriers (from 7.4% in Luxembourg to 49.5% in Greece), which is mirrored by substantial dispersion in the output gains from removing these wedges across countries (from 0.7% in Luxembourg to 7.1% in Canada). However, we find that average immigrant compensation wedges are not a sufficient statistic for determining the output gains from removing immigrant barriers: the correlation between them is 0.47. That is, conditional on a given average level of immigrant compensation wedges, substantial dispersion remains. For example, even if the average magnitude of immigrant compensation wedges in Netherlands (NLD), Spain (ESP), and Belgium (BEL) is almost the same, output gains from removing them are quite different: 4.0 percent in the Netherlands, 5.3 percent in Spain, and 6.9 percent in Belgium.

One candidate explanation for the dispersion in output gains conditional on a given level of immigrant wedges is potential heterogeneity across countries in the share of immigrants in the labor force. For a given level of immigrant wedges, the model implies that countries with larger immigrant populations will feature larger output gains from removing immigrant barriers simply because there are more individuals whose occupation decisions are distorted. We control for this channel in the right panel of Figure 3, where we reproduce the left panel of the figure but plotting real GDP gains per immigrant instead of the total real GPD gains. This adjustment tightens the relation between average immigrant compensation wedges and real GDP gains, increasing the correlation between them from 0.47 to 0.80. In particular, the real GDP gains per immigrant are nearly identical for the Netherlands, Spain, and Belgium despite the much larger differences in the implied total real GDP gains.

Despite the increased correlation between wedges and the gains from removing them, sig-

[24]Each country's immigrant wedges are computed as a simple average across immigrant types, subtypes, and occupations. We focus on simple averages instead of weighting by population given that workers in occupations with high wedges are less likely to choose such occupations, mechanically biasing downwards the estimates of the wedges.

Figure 3: GDP gains from removing immigrant misallocation across countries

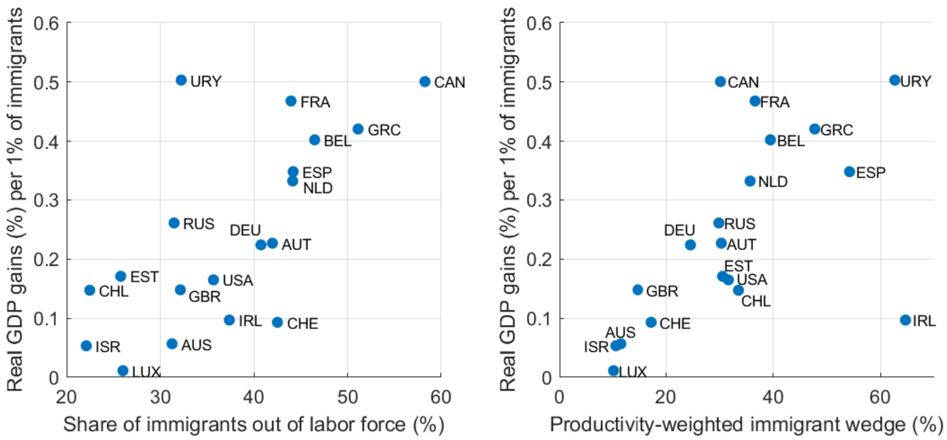


Note: This figure shows how GDP gains from removing immigrant wedges vary across countries. The left panel presents a cross-country comparison of the size of average immigrant wedges and the percent increases in real GDP associated with eliminating the wedge-gap between immigrants and natives. The right panel plots real GDP gains adjusted for immigrant share in the population against the average wedges faced by immigrants.

nificant heterogeneity remains conditional on a given level of immigrant wedges. For example, Austria (AUT) and Canada (CAN) have almost the same average immigrant compensation wedges, but the output gains per immigrant from removing them are more than twice as large in Canada (0.50%) than in Austria (0.23%). Two channels are likely to 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 them — an extensive margin channel. A country with a high fraction of non-employed immigrants is likely to experience a large inflow of workers into the market sector when labor market wedges are alleviated and market occupations become more appealing. Second, the distribution of immigrant wedges across occupations can have a significant impact on the gains from removing immigrant barriers — an intensive margin channel. To the extent that productive occupations are relatively more distorted, then the removal of immigrant wedges leads to an inflow of workers to such occupations, implying larger output gains.

We study the role of these channels in Figure 4. The left panel plots real GDP gains per immigrant as a function of the fraction of immigrants out of the labor force, while the right panel plots the output gains as a function of the average size of immigrant wedges weighted by the estimated productivity A_j of each occupation and the estimated productivity z of each worker type and subtype. We find that both of these channels appear to be significant determinants of the output gains from removing immigrant barriers. First, the left panel shows that there is substantial heterogeneity across countries in the share of immigrants out of the labor force and, moreover, that these are positively correlated with the implied output gains. Second, the right panel shows that output gains from removing wedges are typically larger in countries with larger productivity-weighted immigrant wedges.

Figure 4: Sources of GDP gains from removing immigrant misallocation across countries



Note: This figure shows underlying reasons behind differences in GDP gains from removing immigrant wedges across countries. The left panel presents the share of immigrants out of the labor force among all immigrants against the real GDP gains from removing wedges adjusted by the share of immigrants. The right panel plots the average size of immigrant wedges weighted by the occupation and worker specific productivities against the real GDP gains from removing wedges adjusted by the share of immigrants.

We illustrate how output gains can be driven by either of these channels by turning to two examples. First, compare Canada and Austria, two countries with similar average immigrant compensation wedges as observed in Figure 3), but with considerable differences in the implied output gains per immigrant. We observe that the average productivity-weighted immigrant wedges are the same between them, but Canada has a much larger fraction of immigrants out of the labor force (58% vs. 42% in Austria). This suggests that the larger inflow of immigrants from the home occupation to any of the market occupations is the main driver behind the larger output gains in Canada over Austria. Second, we turn to Germany (DEU) and Switzerland (CHE) which have similarly-sized immigrant compensation wedges and the same fraction of immigrants out of the labor force. Yet, the output gains per immigrant from removing immigrant wedges are much larger in Germany (0.22 percent) than in Switzerland (0.09 percent). This is likely because the productivity-weighted immigrant wedges are larger in Germany (25 percent) than in Switzerland (17 percent). Thus, removing wedges in Germany leads to larger output gains because immigrant wedges are higher in high-productivity occupations and high-productivity workers in Germany.

7 Conclusion

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

We show that the gains from removing immigrant barriers in the U.S. are 2.63 percent of real GDP. These gains arise from both increased market participation among immigrants as well as from an improved allocation of immigrants across market occupations. The gains are also distributed unevenly, with recent immigrants, females, and those who hold STEM and Social

Science degrees poised to benefit the most. Across countries, we find large variation of immigrant distortions and associated GDP gains from reducing misallocation, with the U.S. exhibiting an average level of immigrant barriers and implied gains from removing them.

Our findings have important implications for the design of labor market and immigration policies. Given that immigrant barriers affect the impact of alternative immigration policies, our results suggest that think about these policies jointly might be fruitful to maximize immigrant-specific and aggregate economic potential.

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Appendix for Online Publication

A Data

This section provides details about the main data sets used in the paper, the ACS and the LIS, respectively.

A.1 ACS

In the first part of the paper, we use ACS 2019 data to estimate the model for the U.S. In this section, we provide more details about the data, construction of variables, and the measurement.

In the ACS, we focus on a sample of non-business owner individuals between the ages of 25 and 54 who are not on active military duty.

The ACS provides information on an individual's citizenship and country of birth. Citizenship variable allows us to identify people who are not a U.S. citizen or a naturalized citizen, while the country of birth variable allows us to identify people who born outside of the U.S. Using these variables, we define an immigrant to be a foreign-born individual who is either a naturalized citizen or not a citizen. 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 their time since immigration, English fluency, and income level of their country of origin. First, the ACS provides information on the year in which a foreign-born person entered the U.S. We use this information to classify immigrants into two groups based on their year 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, the ACS also reports how well the respondent speaks 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 Gross National Income (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 uses to divide countries into income groups.[1] In addition to these dimensions of heterogeneity for the immigrants, we also group immigrants and natives into subtypes based on their their level of education, age, and gender.

[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 low income and lower-middle income groups as low income to increase the sample size for this group.

Table A1: Occupation groups and example occupations

	Non-routine, Cognitive	Non-routine, Manual	Routine, Cognitive	Routine, Manual
SOC codes	0010-3540	3600-4650	4700-5940	6200-9750
	Managers	Childcare workers	Cashiers	Construction laborers
	HR/Finance specialist	Janitors	HR assistants	Electricians
	Scientists	Waiters/cooks	Sales/advertising agents	Computer/TV repairers
	Engineers	Nurses	Postal service carries	Maintenance workers
	Doctors	Firefighters	Computer/data entry operators	Flight attendants

Note: This table presents Standard Occupational Classification (SOC) codes in the ACS for broad occupation groups used in our analysis and example occupations for these groups.

Following the literature, we group occupations along two dimensions of the characteristics of tasks required on the job: routine vs non-routine and cognitive vs manual. Following Autor, Levy, and Murnane (2003), an occupation is considered routine if the required tasks of the occupation can be summarized by well-defined instructions and procedures. If tasks in an occupation require more flexibility, human interaction skills, and problem-solving, then the occupation is non-routine. On the other hand, if tasks of an occupation requires more physical activity, it is considered as a manual occupation, while an occupation requiring mental tasks is considered as a cognitive occupation. The ACS provides occupation information of the currently employed workers using the SOC codes. We use these codes (2010 basis) to assign each occupation into one of the four occupations.

A.2 LIS

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

The LIS database provides cross-country survey data that provides individual-level information on labor market outcomes and demographics. The first wave of the LIS data was in 1980 and, until 2000 (Wave 5), the LIS was published in every five years. Starting with Wave 6 in 2004, new data became available in every three years. The latest wave is Wave 11, which collects data between 2018 and 2020. In our analysis, for each country, we use data from a single year, which is the most recent data for which the country has the information necessary to implement our analysis. Furthermore, we restrict our sample to countries in which the share of immigrants among all employed is at least 2 percent. Among 19 countries included in our sample, the data used for 16 countries are between 2015 (Wave 10) and 2019 (Wave 11). We use 2013 data from Wave 9 for Luxembourg because more recent data is not yet available for this country. In addition, we use 2010 data from Wave 8 for Canada and Russia because more recent data does not have occupation information for Canada and immigration information for Russia. In our final sample, we do not use any data prior to 2010 and all data is between 2010 and 2019.

The LIS provides individual-level data on demographics, including the immigration status, and labor market outcomes. Similar to the ACS, we define an immigrant to be a foreign-born individual. 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, occupation, and total annual labor income. Using these information, we follow the same process to construct our empirical moments on labor market allocations and average earnings of each (type, subtype) in all occupations (including the home sector) across countries.

Here, we only discuss the additional details that are specific to our cross-country analysis in LIS. The annual labor income of individuals are provided in nominal local currency. We convert labor income amounts to 2019 US dollars using the PPP and CPI data provided by the LIS. We also unify occupation codes across countries in the following steps. First, the LIS provides two-digit ISCO codes for 13 countries. For these countries, we use the crosswalk between ISCO and SOC codes to obtain SOC codes, which then allows us to assign each occupation into one of the four broad occupation group using the SOC codes these groups presented in Table A1.[2] 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 group; services and sales workers to non-routine, manual occupations; clerical support workers to routine, cognitive occupations; and craft and related workers, plant and machine operators and assemblers, and elementary occupations to routine, manual occupations.[3] 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 ISCO and then between ISCO and SOC. Once we obtain SOC codes for these countries, we use them to assign occupations into one of the four broad occupation group. Finally, for the U.S., the LIS already provides occupation codes based on the Census classification.

Additional results In the main text, Figures 1 and 2 present cross-country differences in allocations and earnings between all immigrants and natives. Here, in Figures A1, A2, and A3, we document how allocations and earnings gaps between immigrants and natives in various gender, education, and age groups differ across countries, respectively.

B Estimation results

[2]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.

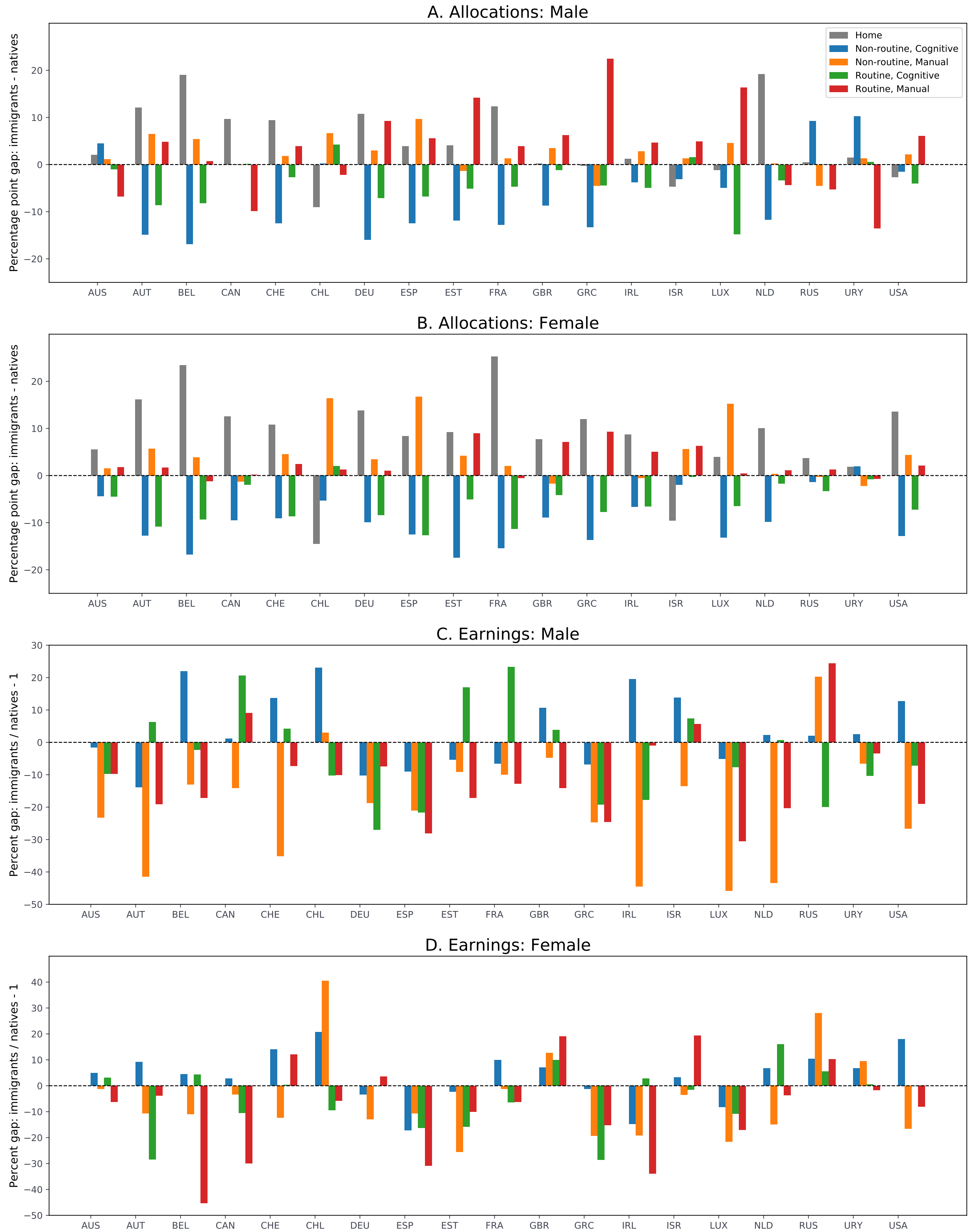
[3]These choices are broadly consistent with the one-digit occupation classifications using the SOC.

Table A2: Estimation results for distribution and earnings

Occupation Type	Distribution						
	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
Non-routine, Cognitive	0.34	0.29	0.28	0.04	0.35	0.38	0.46
Non-routine, Manual	0.10	0.14	0.15	0.19	0.12	0.13	0.07
Routine, Cognitive	0.15	0.09	0.11	0.04	0.12	0.11	0.12
Routine, Manual	0.14	0.16	0.20	0.30	0.16	0.13	0.09
Home	0.26	0.32	0.26	0.43	0.25	0.26	0.26
	Earnings						
Occupation Type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	I_{LIC}	I_{HIC}
Non-routine, Cognitive	1.54	1.64	1.89	1.17	1.84	1.90	2.07
Non-routine, Manual	0.69	0.53	0.63	0.48	0.65	0.62	0.70
Routine, Cognitive	0.94	0.76	0.92	0.61	0.92	0.87	1.14
Routine, Manual	0.95	0.69	0.85	0.63	0.88	0.80	1.04
Home	0.49	0.42	0.46	0.26	0.52	0.51	0.64

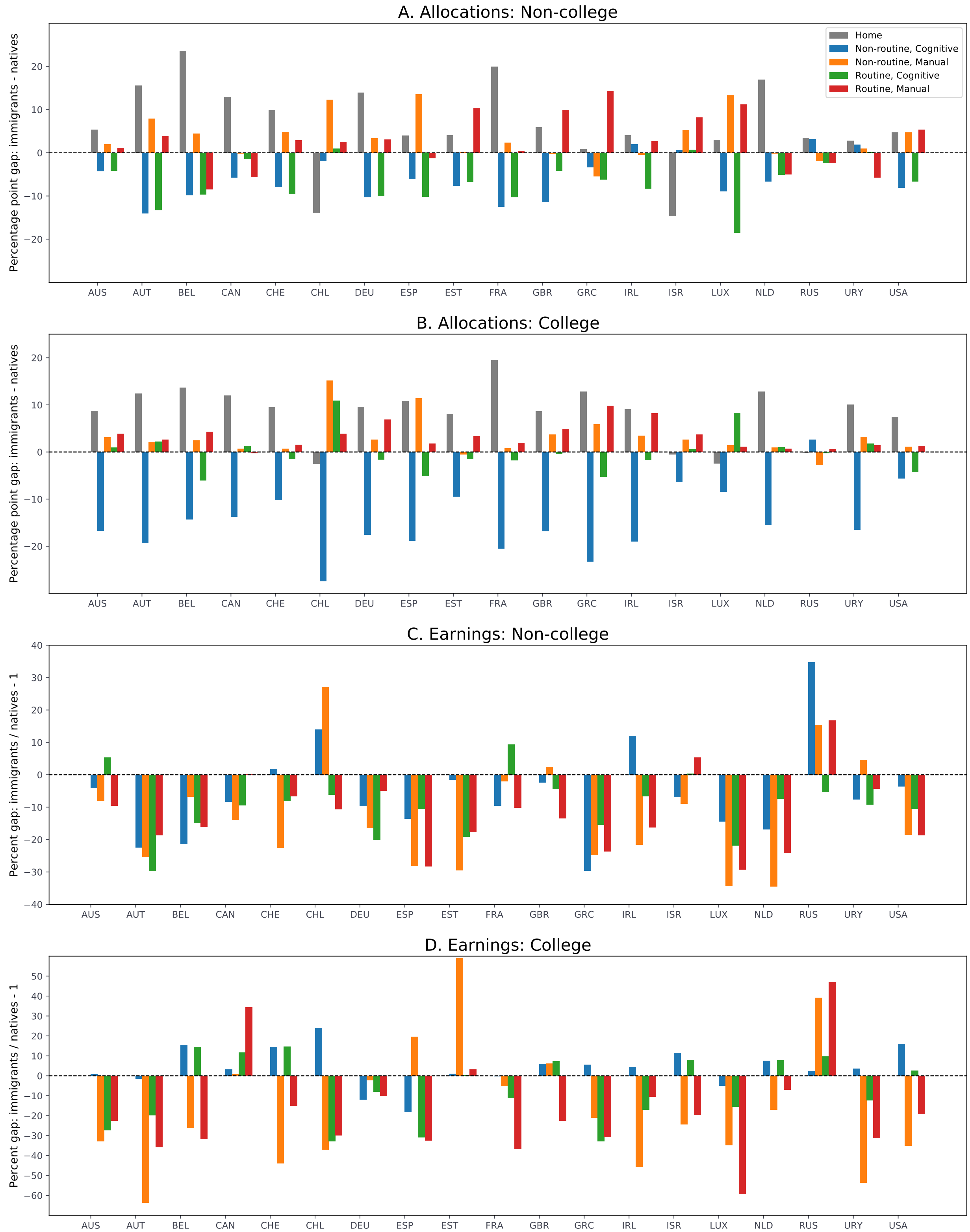
Note: This table presents model-implied targeted moments for the allocation of worker types/subtypes across occupations. We first calculate estimated outcomes for each worker type/subtype and each occupation. For expositional purposes, all aggregated moments are reported for natives and immigrant types across all occupations. The base group of prime-age, male, non-college natives face no wedges to work in any of the market occupations. Worker productivity z is expressed as a multiple of values for the base group. 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.

Figure A1: Differences in allocations and earnings between immigrants and natives: Gender



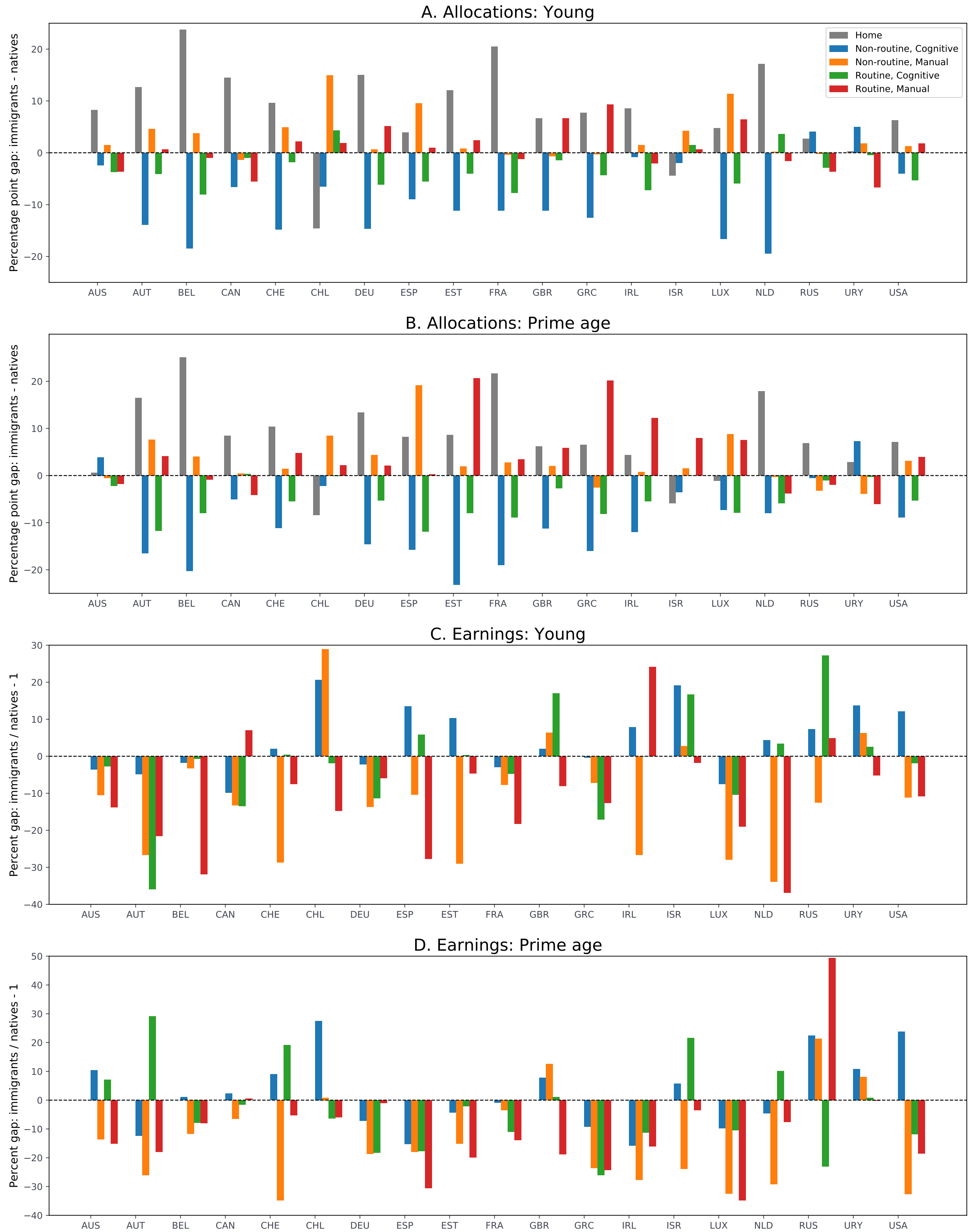
Note: This figure presents differences in labor market allocations and earnings between immigrants and natives across countries for different age groups. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average labor 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 males and females, respectively. Panel C and D show the percent gap (calculated as immigrants/natives − 1) between earnings of immigrants and natives in each occupation across countries for the same gender groups, respectively. Harmonized data on immigration status, employment, income, and demographics are obtained from the Luxembourg Income Study Database.

Figure A2: Differences in allocations and earnings between immigrants and natives: Education



Note: This figure presents differences in labor market allocations and 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 labor 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 without a college degree and with a college degree, respectively. Panel C and D show the percent gap (calculated as immigrants/natives − 1) between earnings of immigrants and natives in each occupation across countries for the same education groups, respectively. Harmonized data on immigration status, employment, income, and demographics are obtained from the Luxembourg Income Study Database.

Figure A3: Differences in allocations and earnings between immigrants and natives: Age



Note: This figure presents differences in labor market allocations and 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 labor 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 young (25-34) and prime age (35-44) individuals, respectively. Panel C and D show the percent gap (calculated as immigrants/natives − 1) between earnings of immigrants and natives in each occupation across countries for the same age groups. Harmonized data on immigration status, employment, income, and demographics are obtained from the Luxembourg Income Study Database.