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

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Abstract

We quantify the barriers to the economic integration of immigrants using an occupational choice model with natives and immigrants of multiple types subject to wedges that distort their allocations. We show that key parameters, including wedges, can be estimated to match the distribution of employment and earnings across individuals and occupations. We find sizable output gains from removing immigrant wedges in the U.S., accounting for 7 percent of immigrants' overall economic contribution. These gains arise from increased labor force participation and from reallocation from manual toward cognitive jobs. We show that the model-implied elasticities are consistent with empirical estimates and that immigrant wedges affect the impact of alternative immigration policies. Finally, we use harmonized microdata across 19 economies and find substantial cross-country differences in the estimated immigrant wedges. Differences in immigrant labor force participation and the correlation between wedges and productivities account for the heterogeneous gains from removing the wedges.

Keywords: Immigration, Occupational Barriers, Mobility, Misallocation
JEL Codes: J24, J31, J61

1 Introduction

Increased immigration holds the potential to be an important source of increased economic well-being across countries. For instance, by boosting countries' labor supply and stock of human capital, immigrants can have a potentially key impact on innovation, growth, and fiscal sustainability. Yet, immigrants often face severe barriers to integrating into foreign labor markets, preventing them from working in the occupations in which they are most productive. Immigrants' productive potential is often limited by occupational regulations and licensing, lack of destination-specific skills, or discrimination, 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.

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

In answering these questions, we make three key contributions. First, we develop a model of occupational choice á la Roy (1951) featuring natives and immigrants, with the latter facing wedges that distort their allocations relative to their native counterparts. Importantly, the model differentiates immigrants along relevant dimensions of heterogeneity, including education, language ability, origin country, and time since immigration. Second, we utilize novel findings on immigrants' labor market allocations and earnings obtained from U.S. and harmonized cross-country microdata to quantify the size of distortions faced by heterogeneous immigrants across countries. Third, we use our U.S. and cross-country estimates of immigrant distortions to understand the macroeconomic gains of removing immigrant barriers, the sources of these gains, and how existing barriers alter the effects of immigration policies that admit immigrants who meet specific characteristics. Critically, these counterfactuals are conducted using a framework that is consistent with prior microeconomic estimates of the labor market effects of changes in immigrant labor supply.

We highlight three novel findings of the paper. First, immigrant barriers in the U.S. are sizable and heterogeneous across individual characteristics and occupations, with their removal resulting in close to a 3% increase in real GDP. Importantly, these gains are achieved through the reallocation of employed immigrants away from manual occupations toward cognitive occupations as well as through the reallocation

of immigrants from non-employment to employment. Second, we find that immigrant barriers are pervasive across countries and often much larger than in the U.S. Importantly, countries with similarly sized average distortions can experience large differences in the gains from barrier reduction due to differences in the incidence of immigrant non-employment as well as in the share of the estimated wedges that affect more-productive occupations or individuals. Finally, we find that the presence of immigrant barriers strongly affects the outcomes of immigration policy reforms. The output per worker gains from admitting high-skilled immigrants are larger in an economy without wedges compared to our baseline economy with wedges. In contrast, when the economy features no wedges, admitting low-skilled immigrants leads to a larger reduction in output per worker, as those immigrants who would have otherwise remained non-employed now find it optimal to participate in market occupations.

Our starting point is to set up a quantitative general equilibrium model populated by natives and immigrants and use it to estimate immigrant barriers and to conduct counterfactual analyses. The model extends the quantitative framework developed by Hsieh, Hurst, Jones, and Klenow (2019) for modeling immigrants, as in Burstein, Hanson, Tian, and Vogel (2020). We consider a closed economy with natives and immigrants of multiple types who choose among alternative labor market occupations or to stay non-employed. Individuals of each type differ in their labor productivity and in their preferences across occupations. Each occupation consists of a producer that hires individuals to produce an occupation-specific good. These goods are then aggregated to produce final goods consumed by all individuals.

In our framework, all individuals, including natives, are subject to (i) compensation wedges modeled as proportional taxes that can vary across occupations and (ii) heterogeneous preferences across occupations. In the model, immigrants differ from natives along two dimensions. First, immigrants face additional immigrant compensation wedges and immigrant labor supply wedges. These wedges are intended to capture 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 either by discouraging employment altogether or preventing the allocation of employed immigrants to their most-productive occupations. Second, the production of occupation-specific goods features imperfect substitution between native and immigrant workers, as estimated by Burstein et al. (2020) and others.

We present findings on the joint distribution of employment and earnings across

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individuals and occupations in the U.S, which we use to estimate the model. In particular, we turn to individual-level data from the American Community Survey (ACS) which provides detailed information about immigrants. We consider multiple types of immigrants partitioned based on time since immigration, English language skills, and the 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 Autor and Dorn (2013) and Cortes, Jaimovich, Nekarda, and Siu (2020).

Our empirical findings reveal large differences in the outcomes between natives and immigrants and within immigrants themselves. For example, immigrants are more likely to work in manual occupations or remain non-employed compared to their native counterparts. With the exception of immigrants from high-income countries, immigrants systematically receive lower earnings in all occupations except for non-routine cognitive jobs. Within immigrants, a longer length of stay, English proficiency, and home country income are all associated with much higher earnings.

We use our model to identify whether these differences reflect fundamental differences in immigrant productivity or barriers that distort immigrants' outcomes. We show that all the key parameters of the model, including wedges and individual productivities, can be estimated to match the joint distribution of employment and earnings across individuals and occupations. In particular, we derive analytical expressions to 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 allows us to obtain sharp insights on the patterns of the data that identify the various wedges and productivities.

Given this approach, we find that the estimated wedges are quantitatively large and vary systematically across individuals and occupations. For instance, immigrants are subject to severe barriers to work in cognitive occupations but substantially lower barriers to work in manual occupations. We also find that immigrant barriers vary systematically by time since immigration and by English proficiency: Recent immigrants and ones with lower English proficiency are estimated to face larger barriers.

In order to understand the macroeconomic implications of immigrant barriers, we contrast our estimated model of the U.S. economy with a counterfactual economy in which all immigrant distortions are removed such that natives and all types of immigrants are subject to the same level of distortions across occupations. We find

that removing immigrant wedges increases real GDP by 2.94%. The output increase results from reallocation along two margins: an increase of employment among immigrants and a reallocation of employed immigrants into more-productive jobs. While the entry of immigrants from non-employment to employment raises their total labor supply in cognitive jobs, productivity decreases in these occupations due to the inflow of individuals who are less productive than those who already chose these jobs *even* in the presence of large wedges. In contrast, the outflow of individuals away from manual jobs leads to an increase in average productivity for these occupations.

We contextualize the quantitative significance of the output gains by comparing the output effects of removing immigrant barriers relative to immigrants' overall contribution to output. To compute the latter, we contrast our model with a counterfactual economy without immigrants and interpret the output difference between them as capturing immigrants' contribution. We find that the gains from removing immigrant barriers are 6.91% of the total contribution of immigrants to U.S. output.

We show that the aggregate implications of removing immigrant barriers differ significantly across individuals and occupations. To do so, we consider a series of experiments in which immigrants wedges are removed one at a time for specific individuals or occupations. These exercises reveal that larger output gains per immigrant result from removing the wedges faced by recent immigrants, female immigrants, and immigrants with degrees in STEM and the social sciences. We find much smaller gains from removing immigrant barriers in non-routine manual occupations. These findings demonstrate that the implications of immigrant barriers are heterogeneous across individuals and occupations, suggesting that policies designed to remove barriers might be more effective if targeted toward certain subsets of the population.

Given the pervasive and heterogeneous nature of immigrant barriers, we then investigate how these barriers affect the outcomes of immigration policies. The gains from the entry of new immigrants — in spite of their skills and potential to fill labor supply gaps in key occupations — may be subdued if barriers prevent their allocation into the most suitable jobs. We first validate our model-implied wage and employment elasticities against empirical estimates from the literature obtained through quasi-natural experiments. In particular, we study the effects of the inflow of Cuban immigrants to Miami in 1980 on the outcomes for natives and immigrants. Using our model, we simulate the inflow of immigrants with the same characteristics as the Cuban immigrants who arrived in Miami in 1980. Consistent with a broad set of

empirical studies, our model implies that the inflow of Cuban immigrants had limited effects on the labor market outcomes of natives but relatively larger effects on the wages of immigrants. 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 after the immigrant shock because (*i*) the newly admitted immigrants are predominantly less educated and they select to work in low-paying occupations and (*ii*) immigrants are perfectly substitutable across types, leading to a decline in average wages of immigrants.

Having verified the model against existing empirical estimates, we use it to study the impact of alternative policies to increase immigration into the U.S. In particular, we study the effects of raising the mass of immigrants through the entry of pools of new immigrants with alternative compositions. We find that 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 policies that admit immigrants without a college degree or immigrants not fluent in English. Importantly, we show that these gains and losses are amplified in the absence of immigrant barriers, implying that immigration policy should also consider immigrant outcomes after entry.

Thus far, we have shown that immigrant wedges are quantitatively significant and vary substantially across immigrant types. In order to enrich our understanding of the underlying drivers of these wedges, we exploit cross-country variation in immigrant allocations and earnings. Our starting point is to use the Luxembourg Income Study (LIS) to combine and harmonize individual-level data 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. This allows us to document novel evidence on how the sizes and distributions of immigrant wedges vary across countries that host a large number of immigrants. Our findings highlight a substantial heterogeneity in the magnitudes and impacts of the barriers faced by immigrants across countries. For instance, countries such as the U.K. and Australia are estimated to feature both low immigrant wedges and effects of wedges on average, while those for European countries such as Belgium, the Netherlands, and Spain are estimated to be much higher. We find that the U.S. features levels of 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 connected with the implied

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

We conclude by verifying whether our estimated immigrant wedges across countries are consistent with external estimates on the degree to which immigrants face labor market barriers in their host countries. We focus on two indexes that capture de facto barriers as reflected in individual's attitudes toward immigrants and de jure barriers as reflected by policies, respectively. We find that our estimates of immigrant wedges are consistent with these indexes, as countries with better attitudes or policies toward immigrants exhibit lower wedges and gains from removing the wedges.

Related literature Our paper contributes to a growing literature that studies the macroeconomic effects of immigration, using structural frameworks (Llull 2018; Burstein, Hanson, Tian, and Vogel 2020; Monras 2020; Albert 2021; Albert, Glitz, and Llull 2021; Albert and Monras 2021; Hanson and Liu 2021; Piyapromdee 2021). These papers develop quantitative models that are disciplined by U.S. microdata to analyze the impact of immigration on wages, occupational choice, migration, inequality, output, and welfare. We follow a similar approach by constructing a framework that accounts for employment and earnings differences of natives and immigrants of different types across occupations, to measure immigrant wedges and quantify the gains from removing them not only for the U.S. but also across countries. To the best of our knowledge, our paper is the first to document empirical patterns on employment and earnings differences of natives and immigrants of various types across occupations in different countries and use these moments to compute immigrant wedges for heterogeneous groups and study their macroeconomic and policy implications.

This paper also contributes to an extensive literature that studies differences in the labor market outcomes of natives and immigrants. Immigrants have been documented to be at a disadvantage in labor markets due to occupational regulations and licensing (Peterson, Pandya, and Leblang 2014), lower bargaining power against em-

ployers (Moreno-Galbis and Tritah 2016), discriminatory practices among recruiters (Oreopoulos 2011), initial gaps in complementary skills and skills mismatch that results in downgrading (Eckstein and Weiss 2004; Dustmann, Frattini, and Preston 2013), and cultural factors (Antecol 2000). These barriers lead to immigrants' poorer labor market outcomes (Abramitzky and Boustan 2017; Arellano-Bover and San 2020; Dostie, Li, Card, and Parent 2020). Our paper complements these studies by quantifying the macroeconomic effects of immigrant wedges that result from these barriers. Our approach relies on using microdata to identify key dimensions of heterogeneity in the sizes of immigrant wedges across demographics and occupations, and importantly, demonstrates how the distribution of immigrant wedges affects key aggregates such as output, employment, productivity, earnings, and labor market allocations.

Finally, 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 represents an increasing share of employment in host countries. We show that immigrants face substantial wedges that distort their labor supply decisions, with significant implications for aggregate outcomes.

This paper is organized as follows. Section 2 presents our model. Section 3 provides details on the data, estimation, and identification. Section 4 provides estimation results and discusses our findings for the U.S. Section 5 studies implications of wedges on immigration policies, and Section 6 extends our analysis to other countries to establish new insights that arise from cross-country comparisons. Section 7 concludes.

2   Model

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

We consider an economy populated by a continuum of individuals and a discrete number of occupations. Individuals choose an occupation 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

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into a final good. Below, we describe the environment in which these agents operate.

2.1 Individuals

Demographics We consider a static model in which individuals live for one period. They are partitioned into types $i = 1, ..., I$ based on their immigration status (e.g., natives and various types of immigrants based on time since immigration, English fluency, and the income level of country of origin). We let $i = 1$ denote natives and $i = 2, ..., I$ denote the set of immigrant types. Individuals of every given type i are further partitioned into subtypes $g = 1, ..., G$ based on observables such as age, gender, and education. We denote the mass of individuals of type i and subtype g by N_{ig}; the total mass of individuals in the economy is 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 work in occupation $j = 0, ..., J$ 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 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.[1] Thus, we have that $\gamma_{1g}^{j} = 0 \ \forall g, j$ since $i = 1$ denotes native individuals. We refer to γ as an "immigrant labor supply wedge" since it distorts immigrants' labor supply decisions across occupations relative to natives conditional on the labor market compensation.

Individual productivity across occupations Individuals are endowed with one unit of labor that they supply to an occupation j, but they 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. Each of these idiosyncratic productivities is distributed Frechet with shape 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 w_{ig}^{j} per effective unit of labor. Yet,

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[1]Hsieh et al. (2019) also introduce type-specific preferences across occupations, to capture differences in social norms across groups.

their labor income is subject to "compensation wedges" that distort their net income and occupational choices. We model compensation wedges as proportional taxes (or subsidies) on the labor income. All individuals of subtype g that work in occupation j are subject to compensation wedge τ_g^j. Immigrants of type $i = 2, ..., I$ are additionally subject to "immigrant compensation wedges" κ_{ig}^j. Thus, $\kappa_{1g}^j = 0 \ \forall g, j$ since $i = 1$ denotes native individuals. We assume that the aggregate revenue collected through these wedges is reimbursed as a proportional subsidy s paid to all individuals.[2]

In this framework, we model two sources of immigrant labor market distortions (i.e., labor supply and compensation wedges) to account for the possibility that occupational choices of immigrants may be distorted even when compensation differences are controlled for. The inclusion of both wedges allows us to capture the fact that immigrants may be prevented from working in certain occupations for two reasons. The first is an intensive margin distortion: immigrants with comparable skills to their native counterparts may be paid less or offered lower positions and salaries due to qualification discounting. The second is an extensive margin distortion: immigrants may be prevented from entering market occupations due to discouragement, discrimination, bureaucracy, or perceived/real qualification gaps.

Occupational choice An individual with a vector of idiosyncratic productivities $(\varepsilon_0, ..., \varepsilon_J)$ chooses occupation j^* that solves the following problem:

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

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

2.2 Occupations

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

We model the difference between market and non-market occupations by assuming that they differ in their production technologies. Production in market occupations is carried out through a nested constant elasticity of substitution (CES) technology that aggregates different types of labor to produce an occupation-specific good. In

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[2]Allocations remain unchanged if wedges are reimbursed via lump-sum transfers.

contrast, production in the non-market occupation is carried out through a linear technology, capturing the idea that the non-market occupation may encompass home production activities that could be carried out independently by each individual.

2.2.1 Market occupations

Production in each market occupation $j = 1, ..., J$ is carried out by a representative firm. Following Burstein et al. (2020), the production technology is a nested CES, with two nests that are aggregated as follows. The outer nest aggregates labor bundles across two groups based on immigration status, natives (individual type $i = 1$) and all types of immigrants (individual types $i = 2, ..., I$), with an elasticity of substitution σ_j. For each of these groups, there is an inner nest that aggregates labor bundles across the various types ($i = 1$ for the the native group and $i = 2, ..., I$ for the immigrant group) and all subtypes g with elasticity of substitution $\widetilde{\sigma}_j$. That is, each inner nest combines individuals across types and subtypes based on demographic characteristics (e.g., age, gender, and education) within a given group based on immigration status (e.g., natives and various types of immigrants).

Outer nest: Aggregation between natives and immigrants The production technology for the outer nest aggregates worker bundles between natives and immigrants with a CES σ_j: $y_j = A_j[n_{\text{nat}}^{j}{}^{\frac{\sigma_j-1}{\sigma_j}} + n_{\text{imm}}^{j}{}^{\frac{\sigma_j-1}{\sigma_j}}]^{\frac{\sigma_j}{\sigma_j-1}}$, where y_j denotes the output produced in occupation j, n_k^j denotes the labor bundle of group k in occupation j, and A_j denotes occupation-specific productivity. We index natives and immigrants with subscripts $k = \text{nat}$ and $k = \text{imm}$, respectively.[3]

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:

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

where p_j denotes the price of the goods produced by occupation j and w_k^j denotes

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[3]We also study two alternative production technologies. First, the outer nest aggregates natives and immigrants across different education levels. Specifically, the outer nest aggregates worker bundles across natives with a college degree, natives without a college degree, immigrants with a college degree, and immigrants without a college degree. Second, the outer nest aggregates labor bundles across natives and all different types of immigrants. In Appendix E, we provide a detailed discussion about the implications of these alternative specifications.

the cost of labor bundle k hired by occupation j.

Inner nest: Aggregation within natives and immigrants The production technology for the inner nest produces 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 CES $\widetilde{\sigma}_j$ for each $k \in \{\text{nat, imm}\}$, where $\mathcal{I}_{\text{nat}} = \{1\}$ and $\mathcal{I}_{\text{imm}} = \{2, ..., I\}$: $n_k^j = [\sum_{i \in \mathcal{I}_k} \sum_{g=1}^G n_{ig}^j{}^{\frac{\widetilde{\sigma}_j - 1}{\widetilde{\sigma}_j}}]^{\frac{\widetilde{\sigma}_j}{\widetilde{\sigma}_j - 1}}$, where n_k^j is the labor bundle of group k in occupation j and n_{ig}^j is the effective units of labor hired from individuals of pair (i, 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 wage rates in occupation j. The problem is then given by:

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

where w_{ig}^j denotes the wage rate per effective unit 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 consists of maximizing profits by choosing the total effective units of labor hired n^0 given the price of the good sold p_0 as well as the occupation-specific wage rate w^0. The problem is given by:

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

2.3 Final good producer

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

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

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

2.4 Equilibrium

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

3 Estimation

In this section, we discuss our data, estimation approach, and identification of key parameters, including wedges.

3.1 Data

We estimate the model using U.S. data from the 2019 ACS. We restrict our sample to non-business owners between the ages of 25 and 54. This sample restriction allows us to focus on working-age individuals, after they finish schooling and prior to retirement. We also drop individuals on active military duty. Appendix B.1 provides details about the data, construction of variables, and measurement.

Individual types We begin by partitioning individuals in the data into the I types of individuals featured in the model, which we index by $i = 1, ..., I$. We let $i = 1$ denote the set of natives and let $i = 2, ..., I$ denote the partition of immigrants based on time since immigration, English fluency, and the home country's income level. We define immigrants as the set of foreign-born individuals.[4]

We partition immigrants' time since immigration based on their arrival year into the U.S. Immigrants with no more than 10 years since immigration are classified as "recent immigrants," and immigrants with more than 10 years are classified as "established immigrants." We partition immigrants' English proficiency based on respondents' self-reported assessment collected by the ACS. We consider three English fluency groups: cannot speak, speaks but not well, and speaks well. Finally, we partition the level of economic development of the immigrants' home country by combining information on respondents' country of birth collected by the ACS with

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

data on each country's gross national income (GNI) per capita for 2019 provided by the World Bank. Using the threshold levels of GNI per capita (in U.S. dollars) that the World Bank uses to divide countries into income groups, we divide countries into three groups: low-income, middle-income, and high-income countries.

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

Individual subtypes We then further partition each individual type $i = 1, ..., I$ 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/medical, or social sciences/humanities/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).

In summary, we classify each individual observed in the data into one of a total of 456 worker (type, subtype) pairs.

Market vs. non-market occupations We allocate individuals between non-market ($j = 0$) and market ($j = 1, ..., J$) occupations following Hsieh, Hurst, Jones, and Klenow (2019). We classify an individual as being in the non-market occupation if the individual is not currently employed or 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. We divide the part-time workers' sample weight equally between the non-market and market occupations.

Market occupations We partition individuals in market occupations into J occupations based on Standard Occupational Classification (SOC) codes, as collected by the ACS. The occupations of these individuals are indexed by $j = 1, ..., J$.

We consider four occupation groups ($J = 4$) based on the skills and types of tasks involved. Following Cortes et al. (2020), we classify occupations into: routine manual,

routine cognitive, non-routine manual, and non-routine cognitive.[5],[6]

Earnings We measure the earnings of individuals as total annual labor income of the respondent in the ACS.[7] 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 (type, subtype) pair, we set the labor income in the non-market occupation to be a fraction λ of the weighted average of income across all market occupations. In particular, we set $\lambda = 0.50$, which falls within the range of estimated replacement rates provided by unemployment insurance in the U.S.[8]

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 individual types i, aggregating across subtypes g. In Section 3.2, we present our estimation approach to match analogous moments for each (type, subtype) pair in each occupation at the most disaggregated level.

The top panel of Table 1 presents the distribution of individuals across occupations. The first column shows the distribution for natives, while the remaining columns show the analogous distributions for immigrant types. Consider the distributions for immigrants by time since immigration, as reported in the second and third columns. We observe that a larger fraction of recent immigrants are in the non-market occupation compared with established immigrants (35% vs. 27%). In addition, both recent and established immigrants are more likely to work in manual occupations than their native counterparts (29% and 34% vs 24%, respectively).

Moreover, English proficiency and the level of economic development of the home country also appear to be systematically related to immigrants' 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 non-employed (i.e., in the non-market occupation). Comparing the sixth and seventh columns, we document that while immigrants from high-income countries and low-income countries are equally likely to be employed in market oc-

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[5]In Appendix E, we show that our main results remain similar if we instead classify occupations into broad groups using a task-intensity index following Autor and Dorn (2013).

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

[7]In Appendix E, we show that our main results remain similar when we use hourly earnings instead of annual earnings as our measure of earnings in the ACS.

[8]Using alternative values of λ does not alter our main results, as we show in Appendix E.

Table 1: Empirical moments

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	0.28	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
Non-market	0.27	0.35	0.27	0.46	0.26	0.28	0.28
Occupation type	Earnings						
	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	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

Note: This table presents the distribution of individuals across market and non-market occupations and their associated labor earnings using data from the 2019 ACS. The distribution of individuals across occupations is conditional on each worker type. Earnings are expressed relative to the average earnings of the base native subtype and occupation: males ages 25 to 34 without college degree and employed in non-routine cognitive occupations. N denotes natives, I_{0-10} denotes recent immigrants ($\leq$ 10 years), I_{10+} denotes established immigrants (>10 years), $I_{\text{Low Eng}}$ denotes low English proficiency immigrants, $I_{\text{High Eng}}$ denotes high English proficiency immigrants, I_{LIC} denotes immigrants originating from low-income countries, and I_{HIC} denotes immigrants originating from high-income countries.

cupations, immigrants from the former group are more likely to work in cognitive occupations than immigrants from the latter group (57% vs 47%).

The bottom panel of Table 1 presents labor earnings of individual types across occupations, where earnings are expressed relative to the average earnings of a base group.[9] Our results reveal significant earnings heterogeneity across individuals and occupations. Critically, we find that all immigrants except those from high-income countries have systematically lower earnings than natives in all except non-routine cognitive occupations, while the average earnings of immigrants from high-income countries are higher than that of natives in all occupations. We also document that longer time since immigration, higher English proficiency, and higher economic development of the home country are all associated with higher earnings.

To summarize, the observations above show that immigrants differ systematically from their native counterparts in their allocations across occupations as well as in

[9]Earnings are expressed relative to the average earnings of the base native subtype and occupation: males ages 25 to 34 without college degree and employed in non-routine cognitive occupations.

their average earnings in these occupations. Our findings also highlight the importance of accounting for the demographics of immigrants given that their labor market outcomes vary substantially across observables. To what extent are these differences in the labor market outcomes of immigrants accounted for by differences in their fundamentals (e.g., preferences, productivity) 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. The parameter space is partitioned into two groups. The first are predetermined and set to standard values from the literature. The second are estimated to match salient features of the data. Table 2 summarizes our estimation approach, listing the predetermined and estimated parameters and the moments used to pin down the latter.

The set of predetermined parameters consists of 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.[10] We set $\sigma_j = \sigma \ \forall j = 1, ..., J$ to simplify the estimation, as it allows us to analytically back out the model's parameters given the target moments. We set the elasticity of substitution between natives and immigrants to 4.6 following Burstein, Hanson, Tian, and Vogel (2020), whose model also features imperfect substitution between natives and immigrants of varying educational attainment and country of origin within occupations. In Section 5.1 we show that the model implies key microeconomic elasticities that are consistent with previous estimates from the literature, lending support for the degree of substitutability across workers of various types implied by our parameterization. These empirical elasticities are analogous to the moments on immigrant and native employment used by Burstein et al. (2020) to estimate the values of σ_j. In addition, we approximate perfect substitution in the inner nest across labor bundles within natives and immigrants by setting $\widetilde{\sigma}_j = 100 \ \forall j = 1, ..., J$.[11]

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

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[10]In Appendix E, we check robustness of our main results under alternative values of η.

[11]We also consider imperfect substitution between workers with different education levels and between immigrants of different types. Further, we check robustness of our results under a different value for σ, as in Burstein et al. (2020). Appendix E provides results under these specifications.

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 worker bundles between natives and immigrants
$\{\widetilde{\sigma}_j\}_{j=1}^J$	100	Elasticity across worker bundles between individual types and subtypes

Estimated parameters

Parameter	# of parameters	Description	Normalization
$\{z_{ig}\}$	455	Individual 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	$\kappa_{1g}^j = 0 \,\forall g, j,\ \kappa_{ig}^0 = 0 \,\forall i, g$
$\{\nu_g^j\}$	96	Preferences	$\nu_g^0 = 1 \,\forall g$
$\{\gamma_{ig}^j\}$	1728	Immigrant labor supply wedges	$\gamma_{1g}^j = 0 \,\forall g, j,\ \gamma_{ig}^0 = 0 \,\forall i, g$
$\{N_{ig}\}$	455	Mass of individuals	$\sum_{i,g} N_{ig} = 1$
$\{A_j\}$	4	Occupation productivity	$A_1 = 1$
Total	4558		

Target moments

Moment	# of moments
Share of individuals (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.

all other individual (type, subtype) pairs is expressed relative to the productivity of the base (type, subtype) (b, ℓ). Second, we assume that individuals 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 compensation wedges to work in any of the market occupations: $\tau_\ell^j = 0$ $\forall j$. Third, we normalize the preference for the non-market occupation such that $\nu_g^0 = 1 \,\forall g$. Fourth, we set immigrant labor supply wedges to zero in the non-market occupation: $\gamma_{ig}^0 = 0 \,\forall i, g$. Fifth, we normalize the total mass of all individuals to be 1 and the productivity of the first market occupation (non-routine cognitive) 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: $\gamma_{1g}^j = 0 \ \forall g, j$ and $\kappa_{1g}^j = 0 \ \forall g, j$.

We use the remaining parameters to target the share of individuals (type, subtype) (i, g) in occupation $j \ \forall i, g, j$, and the average earnings of individuals (type, subtype) (i, g) in occupation j relative to the average earnings of the base (type, subtype) (b, ℓ) in occupation $j = 1$. Throughout the rest of the paper, we set the base (type, subtype) to be given by natives that are males ages 25 to 34 without a college degree and employed in non-routine cognitive occupations (occupation $j = 1$).

3.3 Identification

Given the previously described predetermined parameters, normalizations, and target moments, we back out the remaining parameters directly from the data. Our goal in this section is to describe our approach to backing out these parameters 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 substitution across individuals in the inner nest: $\widetilde{\sigma}_j = \infty \ \forall j = 1, ..., J$. Appendix C provides derivations of the equations used in this section and details about our estimation strategy.

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

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

Preferences and immigrant labor supply wedges Solving the model implies:

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

where Earnings_{ig}^j is 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 (i.e., $\gamma_{1g}^j = 0 \ \forall g, j$) and that the preference for the non-market occupation is normalized to 1 (i.e., $\nu_g^0 = 1$ $\forall g$), we then have that preferences can be backed out from:

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

18

where recall that $i = 1$ denotes natives and Avg. market earnings$_{ig}$ denotes the weighted average of Earnings$_{ig}^j$ across market occupations j, with weights given by the share of individuals of such type and subtype that choose each market occupation.[12] That is, the earnings of natives 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. Using data on natives' earnings in each occupation j for each subtype g and data on natives' average market earnings for each subtype g, this relationship allows us to obtain common preferences $\nu_g^j \ \forall g, j$.

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

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

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

For instance, consider immigrants of type i and subtype g whose earnings in occupation j are much lower than their average earnings across occupations. If their native counterparts of subtype g earn more in occupation j than their average earnings across occupations, then the model attributes the lower relative earnings of immigrants in occupation j to immigrant labor supply wedges in this occupation. Critically, note that these implications are based on the equilibrium outcomes of the model, so other differences between natives and immigrants affect the estimated immigrant labor supply wedges through equilibrium earnings.

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

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[12]Recall from Section 3.1 that, for each (type, subtype) pair, we set the earnings in the non-market occupation to be a fraction λ of the weighted average of income across all market occupations. This implies that Earnings$_{ig}^0 = \lambda \times$ Avg. market earnings$_{ig} \ \forall i, g$.

$$\frac{z_{ig}}{z_{qr}} = \left(\frac{p_{ig}^j}{p_{qr}^j}\right)^{\frac{1}{\eta}} \frac{w_{qr}^j \left(1 - \tau_r^j - \kappa_{qr}^j\right) \text{Earnings}_{ig}^j}{w_{ig}^j \left(1 - \tau_g^j - \kappa_{ig}^j\right) \text{Earnings}_{qr}^j}, \tag{2}$$

where p_{ig}^j denotes the fraction of individuals of type (i, g) that 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 $w_{b\ell}^0 = w_{ig}^0$ given the linearity of the production technology of the non-market occupation. Moreover, we have $\tau_g^0 = \tau_\ell^0 = 0$, $\kappa_{ig}^0 = \kappa_{b\ell}^0 = 0$, and $z_{b\ell} = 1$ given our normalizations. Then, using Equation (2), we have:

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

where Fraction of non-employed$_{ig}$ denotes the share of individuals of type i and sub-type g that are in the non-market occupation. Then, we have that individuals' productivity is identified from differences in average market earnings and the fraction of non-employed relative to the base group. As a result, given data on the fraction of individual (type, subtype) pairs in the non-market occupation and their average market earnings, we obtain their individual productivities $z_{ig} \ \forall i, g$.

The model implies that individuals are estimated to be more productive than the base group if their average market earnings are larger or if they are more likely to be non-employed. 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 individual productivity z. Absent this difference, both types would have the same shares of non-employed individuals and the same average market earnings. But if the types differ in their productivity z, individuals 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 individual (type, subtype) reduces their market wages relative to the wages in the non-market occupation, making them more likely to be non-employed. Quantitatively, the former effect dominates the latter effect, implying that average market earnings are critical to identifying individual 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:

$$\frac{1-\tau_g^j-\kappa_{ig}^j}{1-\tau_r^j-\kappa_{qr}^j} = \left(\frac{p_{ig}^j}{p_{qr}^j}\right)^{\frac{1}{\eta}} \frac{\text{Earnings}_{ig}^j/z_{ig}}{\text{Earnings}_{qr}^j/z_{qr}} \left(\frac{\sum_{k\in\mathcal{I}(i)}\sum_{v=1}^{G}N_{kv}z_{kv}(p_{kv}^j)^{\frac{\eta-1}{\eta}}}{\sum_{k\in\mathcal{I}(q)}\sum_{v=1}^{G}N_{kv}z_{kv}(p_{kv}^j)^{\frac{\eta-1}{\eta}}}\right)^{\frac{1}{\sigma_j}}, \quad (3)$$

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

We back out compensation wedges $\{\tau_g^j\}$ by focusing on natives. Consider natives $(i=1)$ of subtypes g and r, where we set $r=\ell$ to be given by the base subtype. Then, we have $\tau_\ell^j=0$ $\forall j$ and $\kappa_{1g}^j=0$ $\forall g,j$. Thus, Equation (3) 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 given data on earnings and allocations of individual (type, subtype) pairs across occupations and using estimated individual productivities z_{ig} (along with the normalization $z_{1\ell}=1$), we can obtain compensation wedges τ_g^j $\forall g,j$.

This expression implies that the common compensation wedges τ that apply to all natives and immigrants in an occupation j are identified from data on both earnings and participation of natives relative to those of the base (type, subtype) for the given occupation. In particular, natives of subtype g whose earnings in occupation j relative to those of base (type, subtype) are lower than their respective relative productivity between them are inferred to have 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 (type, subtype).

We now proceed to back out immigrant compensation wedges $\{\kappa_{ig}^j\}$. Let (i,g) denote an immigrant of a given type and subtype, and let (q,r) be the base (type, subtype) (b,ℓ). Then, we have $\tau_\ell^j=0$. Moreover, given that we define natives to be the base individual type $(b=1)$, we have $\kappa_{b\ell}^j=0$. Then, Equation (3) becomes:

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

Thus, using data on earnings and allocations of (type, subtype) pairs and fractions of these pairs in the economy, as well as estimated productivities z_{ig} and common compensation wedges τ_g^j, we can obtain immigrant compensation wedges κ_{ig}^j $\forall i,g,j$.

This expression implies that immigrant compensation wedges are identified by

using similar information as used for the common compensation wedges. Conditional on the common compensation wedges, any excess under-participation or under-compensation of immigrants in an occupation beyond that of their native counterparts of the same subtype is interpreted as positive 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 an occupation (relative to productivity), then immigrant wedges κ would be positive. For κ to be zero, immigrants would need to be paid relatively more than natives given their relative scarcity.

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

$$
A_j = \left\{ \frac{\sum_{v=1}^{G} N_{iv} z_{iv} (p_{iv}^j)^{\frac{\eta-1}{\eta}}}{\sum_{v=1}^{G} N_{iv} z_{iv} (p_{iv}^1)^{\frac{\eta-1}{\eta}}} \left[\left(\frac{p_{ig}^j}{p_{ig}^k} \right)^{\frac{1}{\eta}} \frac{z_{ig} \left(1 - \tau_g^1 - \kappa_{ig}^1 \right) (1 + \gamma_{ig}^1) \nu_g^1}{z_{ig} \left(1 - \tau_g^j - \kappa_{ig}^j \right) (1 + \gamma_{ig}^j) \nu_g^j} \right]^{\Phi} \right\}^{\frac{1}{\Phi-1}}. \tag{4}
$$

Note that all objects in this expression can either be computed directly from the data or indirectly using data along with the derivations above. Thus, Equation (4) allows us to obtain occupation productivities $A_j \, \forall j$.

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

4 Immigrant Wedges: Estimates and Impact

In this section, we study the extent and implications of immigrant wedges in the U.S. In Section 4.1, we begin by estimating the parameters of the model following the approach described in the previous section.[13] Our estimated wedges allow us

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[13]Recall that our estimation approach is derived under the restriction that there is perfect substitution across labor bundles in the inner nest. Thus, we estimate the parameters under this restriction and solve the model with $\tilde{\sigma}_j = 100 \, \forall j = 1, ..., J$ to approximate an economy with perfect substitution

to quantify the extent to which immigrants are subject to barriers that distort their labor market outcomes relative to their native counterparts. Next, in Sections 4.2 and 4.3, we analyze the macroeconomic effects of eliminating the immigrant compensation and labor supply wedges, both in the aggregate and across the distribution.

4.1 Estimates of immigrant wedges and productivities

We begin by presenting our estimates of immigrant wedges and productivities in the U.S. Given the large number of parameters of our model (4558 parameters, as described in Table 2), we restrict attention to summary statistics on the estimated parameters for natives as well as for various types of immigrants based on time since immigration, English proficiency, and country of origin. Specifically, Table 3 reports weighted averages of immigrant compensation wedges κ_{ig}^j, immigrant labor supply wedges γ_{ig}^j, and individual productivities z_{ig}. While we focus our discussion on immigrant wedges and individual productivities, we also report estimates of common compensation wedges τ_g^j, common preferences ν_g^j, and occupation productivities 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 that the model closely matches the empirical moments in Table 1.

Overall immigrant wedges and productivities We find that immigrants in the U.S. are subject to significant immigrant barriers that vary systematically across occupations. The top panel of Table 3 shows that immigrants are subject to severe immigrant compensation wedges in cognitive occupations (ranging from 37% to 54% across immigrant types), facing substantially lower immigrant compensation wedges in manual occupations (ranging from 2% to 27% across immigrant types). 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 non-employed. Second, differences in immigrant barriers across occupations distort the allocation of immigrants employed in market occupations.

In contrast, the middle panel shows that immigrant labor supply wedges are estimated to feature lower dispersion across occupations and immigrant types than immigrant compensation wedges. Typically, immigrant labor supply wedges are estimated to be positive in routine occupations and negative in non-routine occupations.

Finally, we observe that immigrants are estimated to be generally less productive

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across labor bundles in the inner nest.

Table 3: Estimation results

| Occupation type | Immigrant compensation wedge κ | | | | | | | Common |
	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	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
Non-market	0	0	0	0	0	0	0	0
	Immigrant labor supply wedge γ							Common
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	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
Non-market	0	0	0	0	0	0	0	1.00
	Individual productivity z							Occupation
Occupation type	N	I_{0-10}	I_{10+}	$I_{\text{Low Eng}}$	$I_{\text{High Eng}}$	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
Non-market	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, common preference shifter ν, immigrant labor supply wedges γ, individual productivity z, and occupation productivity A.

than natives. With the exception of immigrants in non-routine cognitive occupations, the average productivity of immigrants in all other occupations is lower than natives. This finding shows that immigrant labor market under-performance is jointly accounted for by differences in fundamentals between natives and immigrants and by immigrant barriers that distort immigrants' occupational choices.

Immigrant wedges and productivities across immigrant types We now examine the extent to which immigrant wedges differ across immigrant types. Investigating the heterogeneity in wedges 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 individual productivities across immigrants that differ in time since immigration. For recent immigrants, compensation wedges are systematically larger across all occupations

Table 4: Aggregate and sectoral effects of removing wedges

| | Percent change | | | Change in |
Occupation type	Real GDP	TFP	Labor	immigrant share (pp)
Aggregate	2.94	-0.40	3.35	3.76
Non-routine cognitive	4.03	-1.62	5.74	5.54
Non-routine manual	-1.49	3.68	-4.98	-2.61
Routine cognitive	7.15	-2.82	10.26	9.25
Routine manual	-0.43	2.16	-2.53	-0.78

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. 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 market occupations (or each occupation). The change in the immigrant share denotes the percentage point (pp) change in the fraction of immigrants employed in market occupations or each occupation.

and productivity is lower across occupations relative to established immigrants. These patterns are intuitive and consistent with previous studies (e.g., Dostie, Li, Card, and Parent 2020), which point to the time it takes new immigrants to integrate in terms of learning to sidestep any immigrant-specific barriers as well as in terms of increasing their effective productivity in the host country.

We also find systematic differences in immigrant barriers and productivities by English proficiency and the level of economic development of the country of origin. Immigrant compensation wedges in cognitive occupations are higher among immigrants with low English proficiency. In terms of immigrant labor supply wedges, they are estimated to be the most negative among immigrants with low English proficiency and typically the most positive among immigrants from high-income countries. Finally, productivity is estimated to be higher among established immigrants, immigrants with high English proficiency, and immigrants from high-income countries.

4.2 Aggregate implications of immigrant wedges

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

Table 4 presents the effects of removing immigrant wedges on real GDP, TFP,

and employment (labor) both in the aggregate and across occupations. We find that removing the barriers faced by immigrants in the U.S. increases real GDP by 2.94%.[14] This output increase is driven by two channels: (i) an inflow of immigrants from the non-market occupation into market occupations and (ii) the reallocation of workers across market occupations. As a result, the increase of employment is accompanied by a small decline in TFP. This decline in 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. In Table A3, we decompose these two channels by preventing movement of individuals in and out of the non-market occupation and only focus on the reallocation of individuals within market occupations when immigrant wedges are removed. In this case, we find that within-market reallocation of individuals leads to an improvement in aggregate productivity.

Moving to the effects of removing immigrant wedges across occupations, we find heterogeneous impacts across occupations. Output in cognitive occupations increases significantly (4.03% in non-routine cognitive and 7.15% in routine cognitive), while it declines in manual occupations (-1.49% in non-routine manual and -0.43% in routine manual). This pattern mirrors the distribution of immigrant wedges across occupations documented in Section 4.1: Immigrant compensation wedges are significantly larger in cognitive occupations relative to manual occupations.

In tandem with these heterogeneous effects, we find that the underlying 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 the non-market occupation as well as from manual occupations. These workers have lower productivity in these occupations than those who selected into them even before the removal of immigrant wedges, reducing average productivity. Prior to removal of immigrant wedges, the productivity of the former was not sufficiently high to overcome immigrant barriers.

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[14]When we only remove immigrant compensation wedges but keep immigrant labor supply wedges the same as their estimated values, real GDP gains are around 2.90%, implying that almost all the gains are attributable to immigrant compensation wedges.

Quantitative significance We now evaluate the quantitative significance of our findings 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.

Results in Table A4 implies that the real GDP gains from immigration are equal to 42.5% relative to an economy without immigrants. This means that the real GDP gains from removing immigrant wedges are 6.91% of the total gains from immigration (2.94/42.5). Hence, we conclude that removing immigrant wedges significantly increases the overall contribution of immigrants. In particular, their current contribution to the U.S. economy would increase by 6.91% in the absence of wedges.

4.3 Distributional implications of immigrant wedges

In this section, we investigate the distributional implications of immigrant barriers. In particular, we compute the impact of removing only the immigrant wedges faced by immigrants of some type i or subtype g by comparing the baseline model with a counterfactual economy identical to the baseline except that immigrant wedges of the given type or subtype are set to zero. These exercises allow us to shed light on the heterogeneous payoffs associated with the targeted removal of immigrant wedges.

Our findings are reported in Table 5. 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 immigrant types or subtypes 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.

We find significant differences in the effects from removing immigrant wedges across demographic groups. For instance, removing immigrant wedges faced by female immigrants increases real GDP by 0.21% per 1% of the population that is a female immigrant, while the respective value for male immigrants is 0.09%. The removal of wedges for female immigrants results in these females having a larger outflow from the non-market occupation and a larger degree of reallocation within market occupations toward cognitive occupations, as seen in Table A5.

Similarly, larger real GDP gains per immigrant are also observed when immigrant wedges are removed for college graduates. These gains are the largest when wedges

Table 5: Gains from removing wedges by immigrant type/subtype

Category	Immigrant type/subtype	Real GDP (% change)	Share of population (baseline level, %)	Real GDP growth per 1% of imm. (%)
Age	25-34	0.84	5.58	0.15
	35-44	1.03	6.99	0.15
	45-54	0.88	6.45	0.14
Gender	Male	0.79	9.09	0.09
	Female	2.04	9.93	0.21
Education	Non-college	1.59	12.02	0.13
	STEM	0.54	3.08	0.18
	Law or medical	0.08	0.61	0.13
	Social sciences	0.54	3.32	0.16
Duration	Recent immigrants	1.03	5.53	0.19
	Established immigrants	1.79	13.49	0.13
Country of origin	High-income country	0.44	2.44	0.18
	Middle-income country	1.44	10.86	0.13
	Low-income country	0.87	5.72	0.15
English proficiency	No English	0.25	1.26	0.20
	Some English	0.53	3.23	0.17
	Fluent English	2.07	14.53	0.14

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

for immigrants with STEM-related degrees are removed. Table A5 shows that when wedges are removed for STEM graduates, these gains are driven by a large outflow of STEM graduates from the non-market occupation toward market occupations. In this case, all market occupations experience an increase in their immigrant shares, with larger inflows into routine cognitive and non-routine manual occupations. When wedges are removed for social science graduates, we also observe a large outflow from the non-market occupation, but a key difference is that reallocation within market occupations is larger. Similar patterns are observed for law or medical graduates.

Our results also document significant heterogeneity in the effects from removing immigrant wedges across immigrant types. For instance, removing immigrant wedges for recent immigrants and immigrants with the lowest English proficiency also lead to large real GDP gains per immigrant. While these findings suggest that newcomers face significant barriers in the labor market, the smaller gains from removing the

immigrant wedges of established immigrants and those with strong English proficiency suggest that these barriers decay over time.

Finally, we also investigate the degree of heterogeneity in gains 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 of all immigrants in the occupation. Table A6 shows that removing wedges to work in low-productivity occupations (e.g., non-routine manual occupations, where occupation productivity A is estimated to be the lowest) results in a smaller increase of aggregate output, while the opposite is true for high-productivity occupations (e.g., non-routine cognitive occupations, where occupation productivity A is estimated to be the highest). 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 highly desirable from the perspective of aggregate output.

5   Immigration Policy Reform

Thus far, we have shown that the distortions that immigrants face in the labor market cause substantial output losses in the aggregate and that these losses vary across the distribution. A natural question that arises is: to what extent do these barriers affect the outcomes of immigration policies that admit new immigrants of varying characteristics? The gains associated with the admission of new immigrants into the U.S. – no matter how skilled or productive they may be – may be subdued in the presence of barriers that prevent their efficient allocation in the labor market.

We now investigate the implications of immigrant barriers for changes in the stock of immigrants.[15] 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 gains in output per worker arising from the admission of new immigrants into the U.S. differ across immigrant types? Second, how are the returns to increased immigration affected by the 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. as well as about the extent to which the gains from such policies can be amplified by removing immigrant barriers.

Importantly, note that the output and productivity effects of increased immigra-

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[15]Recall that in Section 4, we take as given the current stock of immigrants and focus on the effects of reallocating immigrants currently living in the U.S. across occupations to overcome any immigrant-specific labor market barriers they might be subject to.

tion 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 in Section 5.1. Critically, we compute elasticities in the model that are comparable to empirical estimates obtained from influential microeconomic studies. This exercise allows us to validate the magnitudes of key elasticities in our model. Next, in Section 5.2, we use our model to answer the aforementioned questions on the effects of alternative immigration policies.

5.1 Microeconomic elasticities: Model vs data

To contrast various 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 develop a model experiment that serves as the model-counterpart of these empirical studies. We conclude this subsection by contrasting the model-implied estimates with the empirical estimates.

Empirical estimates Empirical studies on the effects of immigration have relied on a variety of alternative approaches. Dustmann, Schönberg, and Stuhler (2016) argue that only the pure spatial approach, which uses variation in the inflow of immigrants across regions, identifies the total effect of immigration on labor market outcomes of a particular skill group. Thus, analyzing the total effects through a pure spatial approach provides easily interpretable estimates that are policy relevant. We therefore focus on empirical estimates based on the spatial approach.

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

The Marielitos increased the labor force of Miami by around 8 percent at the end

of 1980. They were more likely to be young, male, and with less education: only 18 percent of the Marielitos had a college degree, 55.6 percent were male, and 38.7 percent were young (between ages 21 and 30). Empirical studies used this sudden inflow of immigrants as a quasi-natural experiment to measure how immigrants affect the labor market outcomes of natives. Card (1990) first studies this question, comparing changes in the wages and unemployment rates across demographics between 1979 and 1985 in Miami vis-a-vis those in four cities with similar employment growth as Miami between the late 1970s and early 1980s: 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 in Miami.

Peri and Yasenov (2017) revisit the same experiment and use empirical methods developed over the years since Card (1990). In particular, the choice of control group, i.e., comparison cities, in Card (1990) is based on trends observed after the immigration shock rather than prior to the treatment. Peri and Yasenov (2017) implement a synthetic control method to create a new synthetic city that best resembles the pre-Marielitos labor market in Miami by estimating city weights. In the end, Peri and Yasenov (2017) confirm the early findings of Card (1990) as they find limited changes in the outcomes of native high school dropouts after the immigration shock.[16]

Model-counterpart to empirical estimates We contrast the implications of the model with the effects of the Marielitos shock documented by these studies. 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.[17] 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, 82 percent of the new immigrants

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

[17]Here, we use our model estimated using 2019 ACS data to retain the estimated parameters and wedges that we document in Section 4.1. Results presented in Table 6 remain similar when we instead re-estimate the model using 1980 ACS data for the entire U.S. or for Florida only.

have no college degree; 55.6 percent are male and 44.4 percent are female; and 38.7 percent are classified under the first age group (25-34) and the rest equally divided across the remaining age groups (35-44 and 45-54). These specifications allows us to closely match the education, gender, and age distribution of the Marielitos.[18]

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

Table 6 reports changes in labor market outcomes of natives and immigrants upon the inflow of the Marielitos in both the data and the model.[19] The empirical estimates show that the inflow of Mariel immigrants had limited effects on the outcomes of natives but relatively larger effects on the wages of immigrants in Miami.[20] This result is largely consistent with the 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 for by the imperfect substitutability between immigrant and native labor inputs in the production technology. Imperfect substitution limits the degree to which the rise in immigrant labor supply crowds out the native labor supply. In addition, the rise of the immigrant labor supply leads to an increase in production as the native labor supply also increases slightly. That is, the fraction of natives in the non-market occupation, i.e., the native unemployment rate, slightly declines. An economy that features perfect substitution between immigrants and natives would imply strong crowding-out

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[18]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.

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

[20]We note that empirical estimates 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 for natives and relatively larger for immigrants, a result that is consistent with our model-based estimates.

Table 6: 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 the labor market outcomes of natives and immigrants upon an inflow of immigrants in the data and the model. Empirical estimates are obtained from Card (1990) and Peri and Yasenov (2017), who measure changes in outcomes of natives and previous immigrants after the arrival of Cuban immigrants to Miami in 1980. Using our model, we simulate an analogous inflow of immigrants to obtain model-based estimates.

effects of immigrants on natives, potentially leading natives to experience a large decline in employment and wages. As such, the limited effects of the immigrant shock on native labor market outcomes serves as an external validation for our modeling choice of imperfect substitutability between native and immigrant labor bundles.

On the other hand, our model implies a relatively sizable change in the wages of previous immigrants. Two channels account for this implication. First, as described above, the Mariel immigrants were predominantly less educated. Given that we match this demographic feature of the Mariel immigrants, these new immigrants select into less-productive occupations that pay lower wages, decreasing the average wages of all 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 on the response of labor market outcomes to changes in immigrant labor supply. We now use our estimated model to investigate the potential impact of a broad set of changes to U.S. immigration policy. We focus on policies that increase the stock of immigrants in the U.S. and examine the relative impact of admitting pools of immigrants with various sets of demographics. Critically, we study the extent to which immigrant barriers affect the implied impact of such immigration policy changes.

We consider an inflow of new immigrants that increases the total mass of immigrants by 10 percent — i.e., 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

Table 7: Immigration policy: Productivity gains from admitting new immigrants

Category	Immigrant type/subtype	Baseline model	No immigrant wedge model
All		0.29	0.01
Age	25-34	0.19	-0.02
	35-44	0.43	0.32
	45-54	0.28	0.15
Gender	Male	0.42	0.54
	Female	0.17	-0.30
Education	Non-college	-0.37	-0.88
	STEM	1.26	1.60
	Law or medical	0.63	0.61
	Social sciences	0.70	0.59
Country of origin	High-income country	1.19	1.33
	Middle-income country	-0.03	-0.36
	Low-income country	0.32	0.19
English proficiency	No English	-0.46	-0.85
	Some English	-0.46	-0.81
	Fluent English	0.59	0.58

Note: This table presents percent changes in output per worker (TFP, in our model) when we increase the total mass of a given recent immigrant (type, subtype) pair such that the total mass of all immigrants in the economy increases by 10 percent. The first column shows percent changes in 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).

impact on total output. We contrast alternative approaches to increasing immigration by considering different compositions of the pool of new immigrants, as we describe below in detail. The first column of Table 7 shows percent changes in output per worker in an economy with immigrant wedges (baseline model) when we implement these alternative policies one at a time. The second column repeats this exercise in an economy without immigrant wedges (no immigrant wedge model).

We begin by examining the effects of these policies in the baseline model. The first row of the table reports the effects of increasing immigration as described above when considering a pool of new immigrants whose distribution across types and subtypes is identical to the current distribution of recent immigrants in the U.S. We find that this policy change increases output per worker by 0.29%. That is, we find that new immigrants not only mechanically increase the stock of potential workers, but they also increase the effective productivity of the overall stock of workers.

We also find that the impact of increasing immigration differs substantially de-

pending 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 a particular demographic or immigrant types.[21] For instance, if the U.S. implements an immigration policy that only admits immigrants with no college degree or immigrants who are not fluent in English, output per worker declines by around 0.5%. On the other hand, when the immigration policy favors those with a college degree, output per worker increases significantly, ranging from 0.63% for a law or medical degree to 1.26% for a STEM degree — which are akin to an expansion of the H1B visa policy in the U.S. Among age groups, we find that the highest gains are achieved when the immigration policy targets individuals in the middle age group (35-44), implying that productivity gains exhibit an inverse-U-shaped pattern in age.

The second column of Table 7 shows that the impact of increased immigration depends critically on the extent to which immigrants are subject to barriers. In particular, we find that the gains from admitting immigrants with a college degree from a STEM field or from high-income countries are amplified when immigrants are brought into an economy with no immigrant-specific distortions. In an economy with no immigrant wedges, new immigrants allocate to 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 in the non-market occupation (i.e., non-employed) given their low productivity in market occupations. However, without immigrant wedges, a higher fraction of such new immigrants enter market occupations, leading to a larger drop in output per worker.

These findings show that that productivity gains from increased immigration vary greatly depending on the composition of the new immigrant pool and that there are asymmetric effects of removing immigrant wedges when new immigrants are admitted into the U.S. depending on the composition of the new immigrant pool.

6 Immigrant Wedges Across Countries

The previous sections demonstrated that the immigrant barriers in the U.S. have sizable aggregate, distributional, and policy implications. The quantitative signifi-

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[21]We assume that the distribution of new immigrants across the remaining types and subtypes is the same as in the overall U.S. distribution of recent immigrants.

cance of these barriers motivates a deeper understanding of the underlying drivers of immigrant wedges and the gains associated with their removal. In this section, we exploit cross-country variation in immigrant allocations and earnings to achieve two objectives. First, we document the magnitudes of immigrant wedges and their macroeconomic implications across countries. Second, we use cross-country differences in immigrant labor markets and distortions to provide evidence on underlying labor market features that determine the gains from removing immigrant wedges.

Data We use cross-country survey data from the Luxembourg Income Study (LIS) database, which collects information from surveys originally conducted by national institutions in each respective country. The LIS publishes data in waves that are typically three to five years apart. For each country in the LIS database, we 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 of the LIS, which cover the period from 2015 to 2020.[22]

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.[23] To maximize the comparability of empirical targets across countries and, at the same time, to keep the empirical implementation as similar as possible to our analysis using the ACS in Section 3.1, we make the following choices in the LIS data.

First, individuals are partitioned into types and subtypes as in Section 3.1, which used the ACS, but with a few exceptions. Given data limitations, we abstract from differences across immigrants by time since immigration, fluency in the language of the host country, and the income level of the country of origin. Further, we maximize comparability across countries by considering two education categories, i.e., non-college vs. college. 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 is at least 2 percent. As in the ACS, we restrict our sample to non-business owners between the ages of 25 and 54 who are not on active military duty.

Second, the LIS database provides information on the current occupation of em-

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

[23]Similar to the ACS, we define an immigrant to be a foreign-born individual. Moreover, 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 into 2019 U.S. dollars.

ployed individuals, where occupations for each country are based on either the International Standard Classification of Occupations (ISCO) codes or the country's own occupation classification. We map each country's occupation classification into the SOC by using crosswalks between the ISCO and SOC for countries with ISCO codes, and crosswalks between country-specific occupation codes and the ISCO and then between the ISCO and SOC for the remaining countries. We then classify each individual's reported occupation into one of the four task-based occupation categories, similar to the implementation in Section 3.1.[24] This process allows us to harmonize the classification of occupations into broad occupation groups across countries.
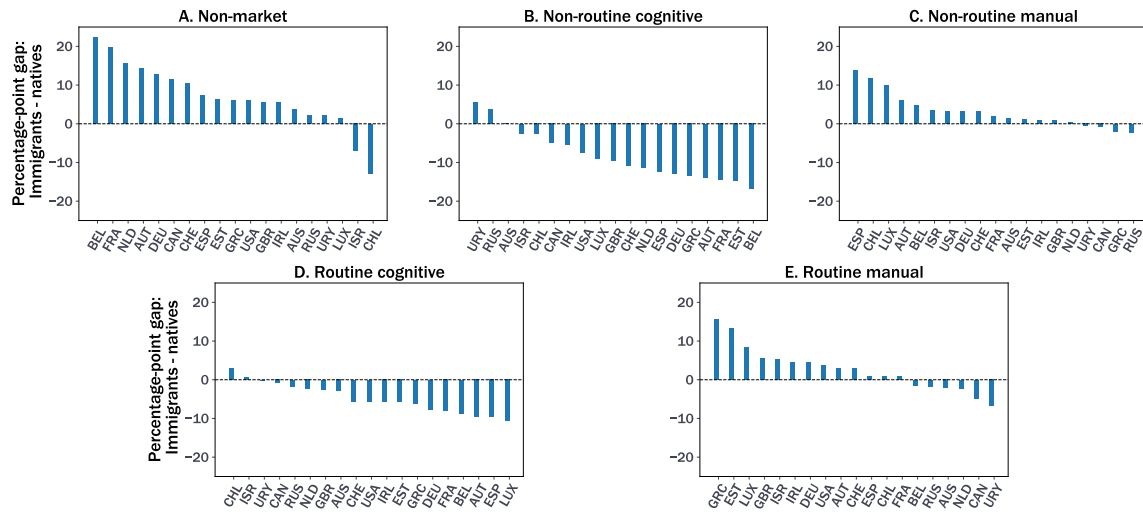
Our final sample consists of 19 countries with harmonized target moments on the distribution and earnings of individuals across demographics and occupations. Appendix B.2 provides more details about the data and measurement.

Labor market outcomes of immigrants across countries We start by documenting salient differences in labor market outcomes between immigrants and natives across countries. We focus on the distribution of immigrants and natives across occupations and their average labor earnings in each occupation since these are the moments used to estimate the model. Specifically, for each country, we first calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as their associated average labor earnings in each occupation. Then, for each occupation we calculate (i) the percentage-point gap (expressed as immigrants$-$natives) between the fraction of immigrants and natives that choose it and (ii) the percent gap (expressed as immigrants/natives $-$ 1) between the earnings of immigrants and natives. Figures 1 and 2 plot these two moments across countries, respectively.

We highlight salient differences across countries in the allocation of immigrants and natives across occupations. First, while the fraction of immigrants in the non-market occupation is higher than that of natives in almost all countries, this gap varies significantly across countries. For example, while this gap is 6 percentage points (pp) in the U.S. (USA) 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 earn-

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

Figure 1: Cross-country differences in allocations between immigrants and natives
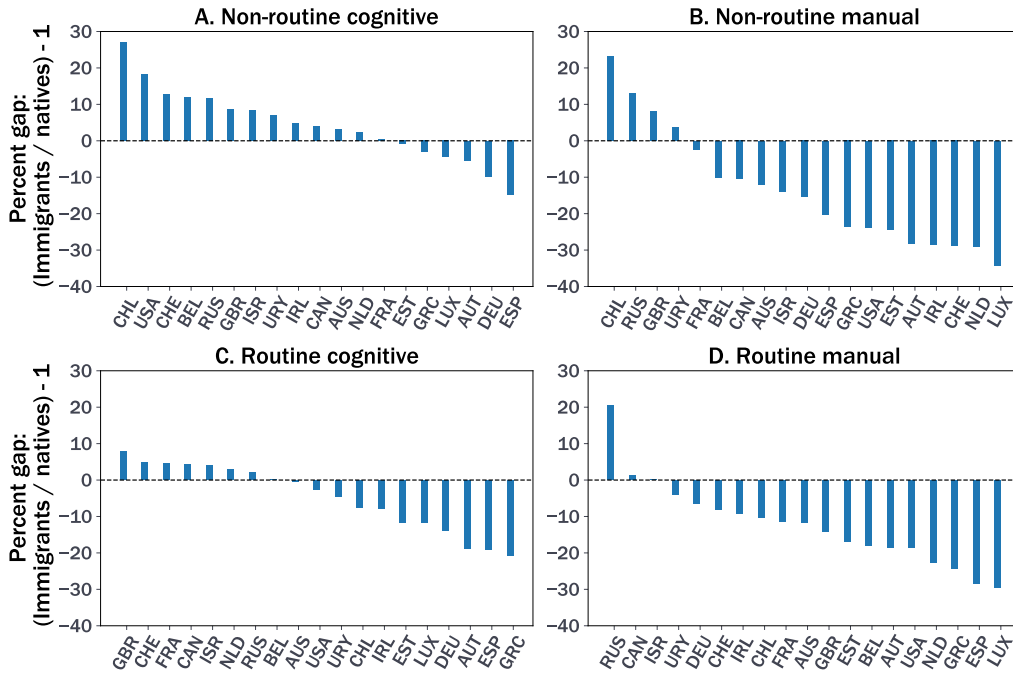
ings in all countries) and overrepresented in non-routine manual occupations (the occupation with the lowest average earnings in all countries) in almost all countries. Notably, there are sizable differences in the gaps between the fractions of immigrants and natives in these occupations across countries. For instance, while the fraction of immigrants in non-routine cognitive occupations is 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 in the U.S., immigrants are overrepresented in these occupations in Spain (ESP) and Chile (CHL).

Moving to the earnings gaps between immigrants and natives, Figure 2 shows that these vary 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 those of natives in non-routine cognitive occupations, exhibiting significant dispersion across countries. For example, in these occupations, the average earnings of immigrants are 18 percent larger than those of natives in the U.S. but 15 percent and 10 percent lower than those of natives in Spain and Germany, respectively. On the other hand, the average earnings of immigrants are significantly lower than those of natives in non-routine manual occupations across most countries, but the magnitudes

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

A. Non-routine cognitive

B. Non-routine manual

C. Routine cognitive

D. Routine manual

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

of these earnings gaps exhibit large heterogeneity: immigrants in these occupations earn 24 percent less than natives in the U.S., 15 percent less than natives in Germany, and 11 percent less than natives in Canada.

We note that differences in labor market allocations and earnings between immigrants and natives across countries can be driven by differences in their demographics. In Appendix B, 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 wedges across countries: Estimates and aggregate effects The evidence above shows that differences in the labor market outcomes between immigrants and natives vary substantially across countries. We now investigate the extent to which these differences reflect differences in immigrant wedges across countries or are accounted for by cross-country differences in immigrants' productivities or pref-

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

The left panel of Figure 3 presents the relation between the average of the immigrant compensation wedges across countries (x-axis) and the real GDP gains from removing immigrant wedges (y-axis).[25,26] We find that there is a large degree of dispersion in immigrant barriers (from 7.4% in Luxembourg (LUX) to 49.5% in Greece (GRC)), which is mirrored by substantial dispersion in the output gains from removing these wedges across countries (from 1.3% in Uruguay (URY) to 8.4% in Canada).[27] However, we find that the average immigrant compensation wedges is not a sufficient statistic for determining the output gains from removing immigrant barriers: the correlation between them is 0.39. That is, conditional on a given average level of immigrant compensation wedges, substantial dispersion remains. For example, even if the average immigrant compensation wedges in Netherlands (NLD), Spain (ESP), and Belgium (BEL) are almost the same, output gains from removing immigrant wedges are quite different: 4.8% in the Netherlands, 6.1% in Spain, and 7.6% in Belgium.
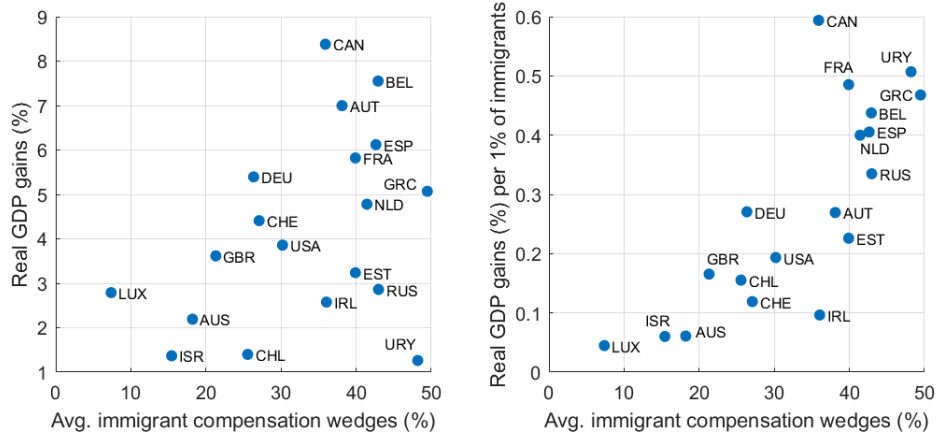
One explanation for the dispersion in gains conditional on a given level of the average immigrant wedges is heterogeneity across countries in the share of immigrants in the population. For a given level of wedges, the model implies that countries with larger immigrant populations feature larger gains from removing wedges simply because there are more individuals whose occupational choices are distorted. We control for this channel in the right panel of Figure 3, where we reproduce the left panel of the figure but instead plot GDP gains per immigrant instead of the total GDP gains. This adjustment tightens the relation between average immigrant compensation wedges and GDP gains, increasing the correlation between them from 0.39 to 0.79. The gains per immigrant now become nearly identical for the Netherlands, Spain, and Belgium despite the much larger differences in the implied total gains.

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

[26]Each country's immigrant compensation 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 individuals in occupations with high wedges are less likely to choose such occupations, mechanically biasing downwards the estimates of the wedges.

[27]Notice that real GDP increases by 3.86% in the U.S., which is close to our estimate of 2.94% when the model is estimated using the ACS, as shown in Table 4. This difference between the estimated GDP gains from removing wedges in the U.S. using the ACS and the LIS is expected given that when we estimate the model using the LIS data; we do not account for immigrant types and consider only two education categories due to data limitations across most countries.

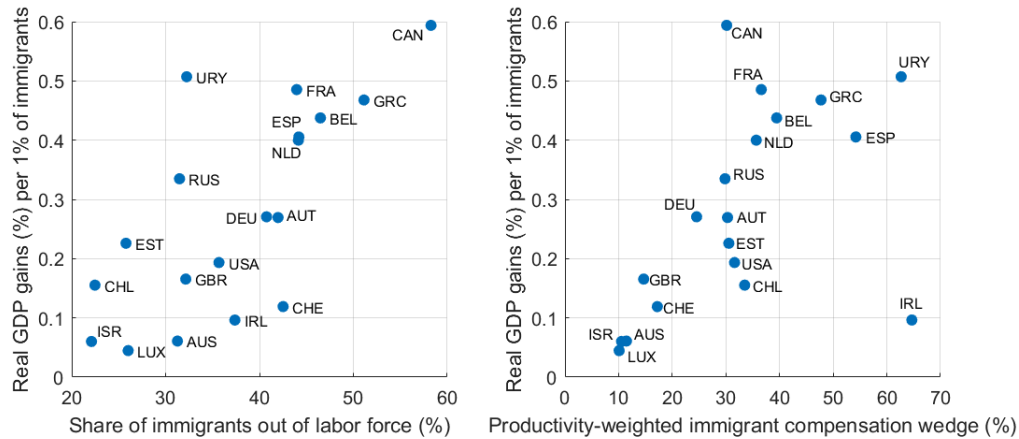Figure 3: GDP gains from removing immigrant wedges across countries

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

Despite the increased correlation between wedges and the gains from removing them, significant heterogeneity remains conditional on a given level of immigrant wedges. For example, Austria (AUT) and Canada (CAN) have almost the same average immigrant compensation wedges, but the gains per immigrant from removing immigrant wedges are more than twice as large in Canada (0.59%) than in Austria (0.27%). Two channels likely play a significant role in accounting for this residual heterogeneity. First, the gains from removing immigrant barriers depend on the share of immigrants that are non-employed prior to removing the barriers — an extensive margin channel. A country with a high fraction of non-employed immigrants is likely to experience a large inflow of individuals into market occupations when wedges are alleviated and market occupations become more appealing. Second, the distribution of immigrant wedges can have a significant impact on the gains from removing immigrant barriers — an intensive margin channel. To the extent that more-productive occupations or individuals are relatively more distorted, the removal of wedges leads to a reallocation of workers to such occupations, implying larger 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 (i.e., in the non-market occupation), while the right panel plots the gains as a function of the average of the immigrant compensation wedges weighted by the estimated productivity A_j of each occupation and the estimated productivity z of each individual

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

Note: This figure shows the underlying channels that account for differences in GDP gains per immigrant from removing immigrant wedges across countries. The left panel presents the relation between the share of immigrants out of the labor force among all immigrants and the GDP gains from removing immigrant wedges adjusted by the share of immigrants. The right panel plots the relation between average immigrant compensation wedges weighted by the occupation and individual specific productivities and the GDP gains per immigrant.

type and subtype. We find that both of these channels are important determinants of the gains from removing immigrant wedges. First, the left panel shows that there is substantial heterogeneity across countries in the share of immigrants out of the labor force and, moreover, that these are positively correlated with the implied gains. Second, the right panel shows that gains from removing wedges are typically larger in countries with larger productivity-weighted immigrant wedges.

Two examples illustrate how output gains can be driven by either of these channels. For the first, we 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 larger fraction of immigrants out of the labor force (58% vs. 42% in Austria). This suggests that the larger inflow of immigrants from the non-market occupation to market occupations is the main driver behind the larger gains in Canada over Austria. For the second, we turn to Germany and Switzerland (CHE), which have similarly sized immigrant compensation wedges and similar fractions of immigrants out of the labor force. Yet, gains per immigrant from removing wedges are larger in Germany (0.27%) than in Switzerland (0.12%). This is because the productivity-weighted wedges are larger in Germany (25%) than in Switzerland (17%). Thus,

Table 8: Immigrant barriers across countries: Model estimates vs. external evidence

| | Correlations between model outcomes and external estimates | | | |
| | Avg. immigrant comp. wedge | | Output per worker (% change) | |
	MAI	MIPEX	MAI	MIPEX
Aggregate	-0.46*	-0.26	-0.49*	-0.28
Non-routine cognitive	-0.30	-0.08	-0.47*	-0.10
Non-routine manual	-0.42*	-0.22	0.22	-0.02
Routine cognitive	-0.42*	-0.28	-0.27	-0.08
Routine manual	-0.25	0.05	-0.27	-0.35

Note: Star superscripts denote statistical significance at the 10% level. MAI denotes the Migrant Acceptance Index reported in the second column of Table 4 in Fleming et al. (2018). MIPEX denotes the Migrant Integration Policy Index from Solano and Huddleston (2020).

removing wedges in Germany leads to larger gains because immigrant wedges are higher for high-productivity occupations and high-productivity workers in Germany.

Immigrant barriers across countries: Model vs. external evidence We conclude the cross-country analysis by comparing model-implied estimates of immigrant wedges with external evidence on the degree to which immigrants face barriers.

We focus on two measures of immigrant barriers implied by our model: average immigrant compensation wedges and the growth of output per worker upon removal of immigrant wedges. The former captures the extent to which immigrants' choices might be distorted, while the latter captures the aggregate impact of such distortions.

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

To contrast the model-implied measures of immigrant wedges with these external estimates, we compute the correlation between them for the 17 countries for which these indexes overlap with the set of countries that we study. Table 8 reports these

correlations for wedges and output gains both in aggregate and across occupations.

We find that the model-implied estimates of immigrant barriers are consistent with the external indexes that we study. In particular, we find that the vast majority of the correlations are negative, reflecting that countries with better attitudes or policies toward immigrants (i.e., higher values of the external indexes) are estimated to feature lower wedges and gains from their removal. Note also that, despite the limited number of observations, we find that the correlation between the MAI and the aggregate model-implied estimates are statistically significant at the 10% level.

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. is around 3% of GDP. These gains arise from both increased labor market participation among immigrants as well as from the improved allocation of immigrants across occupations. The gains are also distributed unevenly, with recent immigrants, females, and those who hold STEM or social science degrees poised to benefit the most. Across countries, we find large variations in immigrant wedges and associated gains from removing them, with the U.S. exhibiting a level of immigrant wedges and implied gains from removing them close to the averages across the countries in our sample. We show that the gains from removing these wedges are determined by the prevalence of immigrant non-employment as well as the concentration of large wedges for high-productivity occupations and high-productivity workers.

Our findings have important implications on the outcomes of labor market and immigration policies. Given that immigrant barriers affect the impact of alternative immigration policies, our results suggest that policymakers should jointly address immigrant entry as well as labor market integration *after* entry.

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

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Online Appendix

A Model

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

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

A *competitive equilibrium* consists of prices $\left(p, \{p_j\}_{j=0}^{J}, \{w_{ig}^{j}\}_{i,g,j>0}, \{w_k^{j}\}_{k\in\{\text{nat,imm}\},j>0}, w^0\right)$ 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 $\{w_{ig}^{j}\}_{j=1}^{J}$ and w^0, $\mathcal{O}_{ig}(\alpha)$ solves the problem of each individual of type i, subtype g, and productivity vector α.

2. Given price p_j and wages $\{w_k^{j}\}_k$, y_j and $\{n_k^{j}\}_k$ solve the problem of the representative firm in the outer nest of each market occupation $j = 1, ..., J$.

3. For each group $k \in \{\text{nat,imm}\}$, given wages w_k^{j} and $\{w_{ig}^{j}\}_g$, 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 producer.

6. Aggregate revenue collected through compensation wedges is equal to aggregate reimbursements distributed to individuals:

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

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

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

1

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

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

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

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

B   Data

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

B.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 measurement.

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

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

In our analysis, we consider an economy where immigrants are divided along various dimensions such as time since immigration, English fluency, and the income level of the country of origin. First, the ACS asks asks the year a foreign-born individual immigrated to the U.S. We use this information to classify immigrants into two groups based on the number of years since immigration: recent immigrants, whose years since immigration is less than or equal to 10 years, and established immigrants, whose years since immigration is higher than 10 years. Second, 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 GNI per capita data from the World Bank. We define low-income countries as those whose GNI per capita is less than $3,995 in 2019 U.S. dollars, middle-income countries as those whose GNI per capita is between $3,995 and $12,375, and high-income countries as those whose GNI per capita is higher than $12,375. These cutoffs are the values that the World Bank used in 2019 to divide countries into income groups.[1] In addition to these dimensions of heterogeneity for the immigrants, we also group immigrants and natives into subtypes based on their education, age, and gender.

Following the literature, we group occupations along two dimensions of the characteristics of tasks required for the job: routine vs. non-routine and cognitive vs. manual. Following Autor et al. (2003), an occupation is considered routine if the required tasks of the occupation can be summarized by well-defined instructions and procedures. If the tasks require more flexibility, human interaction skills, and problem-solving, then the occupation is considered non-routine. Additionally, if the tasks require more physical activity, it is considered a manual occupation, while if the tasks require more mental activity, it is considered a cognitive occupation. The ACS provides occupation information of the currently employed, using the SOC codes. We use these codes (2010 basis) to assign each occupation into one of the four occupations as in Cortes et al. (2020). Table A1 provides SOC codes for each of these groups and lists several example occupations in each group.

B.2 LIS

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

The LIS provides cross-country survey data with individual-level information on labor market outcomes and demographics. LIS data were published every five years from Wave 1 in 1980 to Wave 5 in 2000. Starting with Wave 6 in 2004, new data

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

Table A1: 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 the broad occupation groups used in our analysis and example occupations for these groups.

became available every three years. The latest wave is Wave 11, which collected 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. Moreover, we restrict our sample to countries in which the share of immigrants among all employed is at least 2 percent. The data for 16 countries in our sample are between 2015 (Wave 10) and 2019 (Wave 11). We use 2013 (Wave 9) data for Luxembourg because more recent data is not yet available. In addition, we use 2010 (Wave 8) data 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 database provides individual-level data on demographics, including immigration status and labor market outcomes. Similar to the ACS, we define immigrants to be foreign-born individuals. In terms of labor market related variables, the LIS contains individual-level data on employment status (employed or non-employed), self-employment status, usual hours worked in a week, occupation, and total annual labor income. Using this 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 non-market occupation) across countries.

Here, we only discuss the additional details that are specific to our cross-country analysis using the LIS. The annual labor income of individuals is provided in nominal local currency. We convert labor income amounts to 2019 U.S. dollars using the PPP and CPI data provided by the LIS. We also unify occupation codes across countries in the following steps. First, the LIS database provides two-digit ISCO codes for 13 of 19 countries in our sample. For these countries, we use the crosswalk
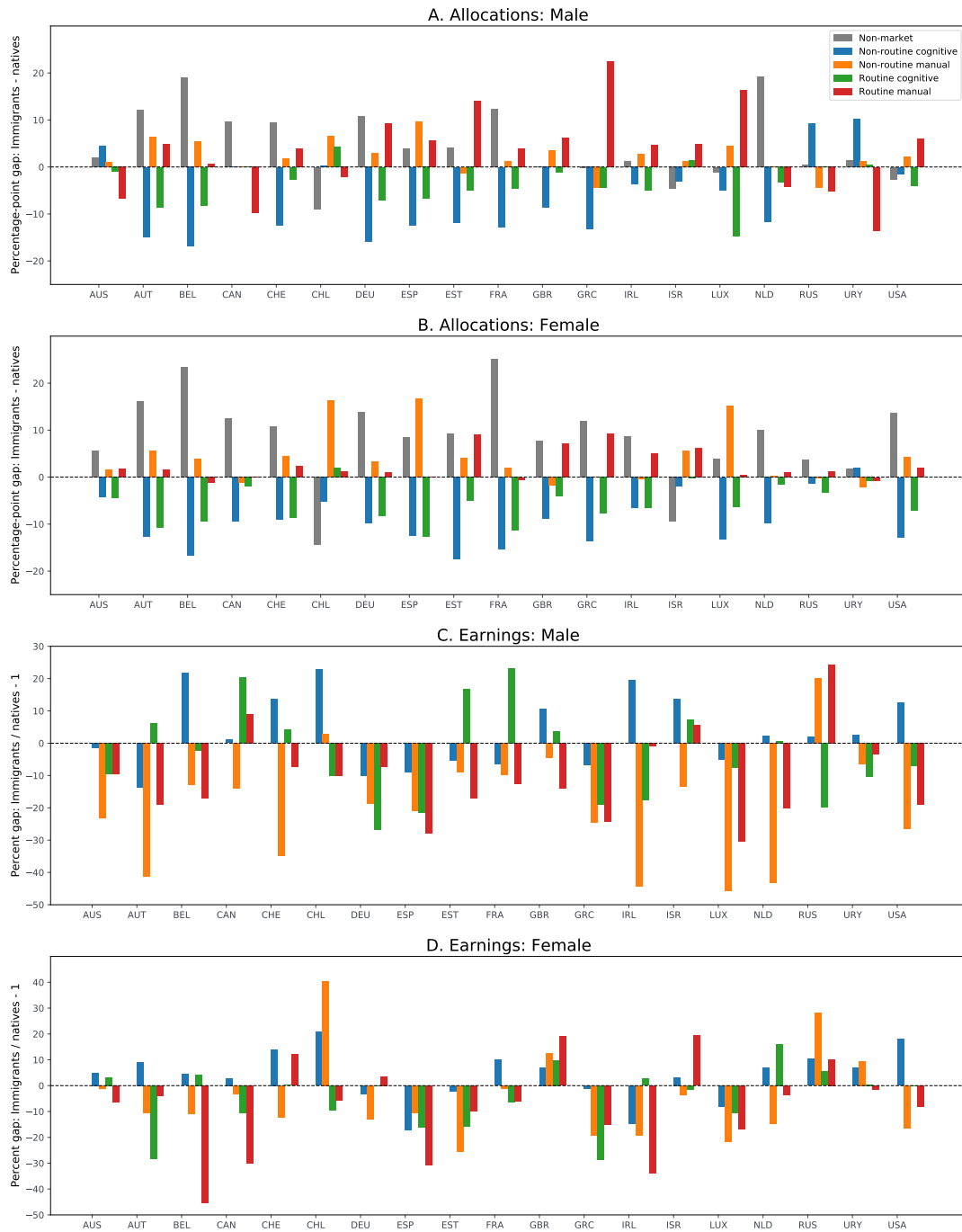
between the ISCO and SOC codes to obtain SOC codes, which then allows us to assign each occupation into one of the four broad occupation group using the SOC codes of these groups presented in Table A1.[2] Second, for Greece, Israel, and the U.K., the LIS only provides one-digit ISCO codes. Using this 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 the ISCO and then between the ISCO and SOC. Once we obtain SOC codes for these countries, we use them to assign occupations into one of the four broad occupation groups. 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. We highlight the following observations. First, in the U.S., the fraction of male immigrants in non-routine cognitive occupations is similar to that of male natives. In contrast, the fraction of male immigrants in these occupations is significantly lower than that of male natives in most other countries. On the other hand, a salient feature across almost all countries is that there is a much larger fraction of female immigrants in the non-market occupation than female natives in that occupation. Second, in terms of earnings, the average earnings of immigrants with a college degree in non-routine cognitive occupations is higher than those of natives with a college degree in the majority of countries, but the opposite is true for non-college workers. On the other hand, in routine cognitive occupations, while the average earnings of non-college immigrants is lower than those of non-college natives in the majority of countries, college immigrants earn more than college natives

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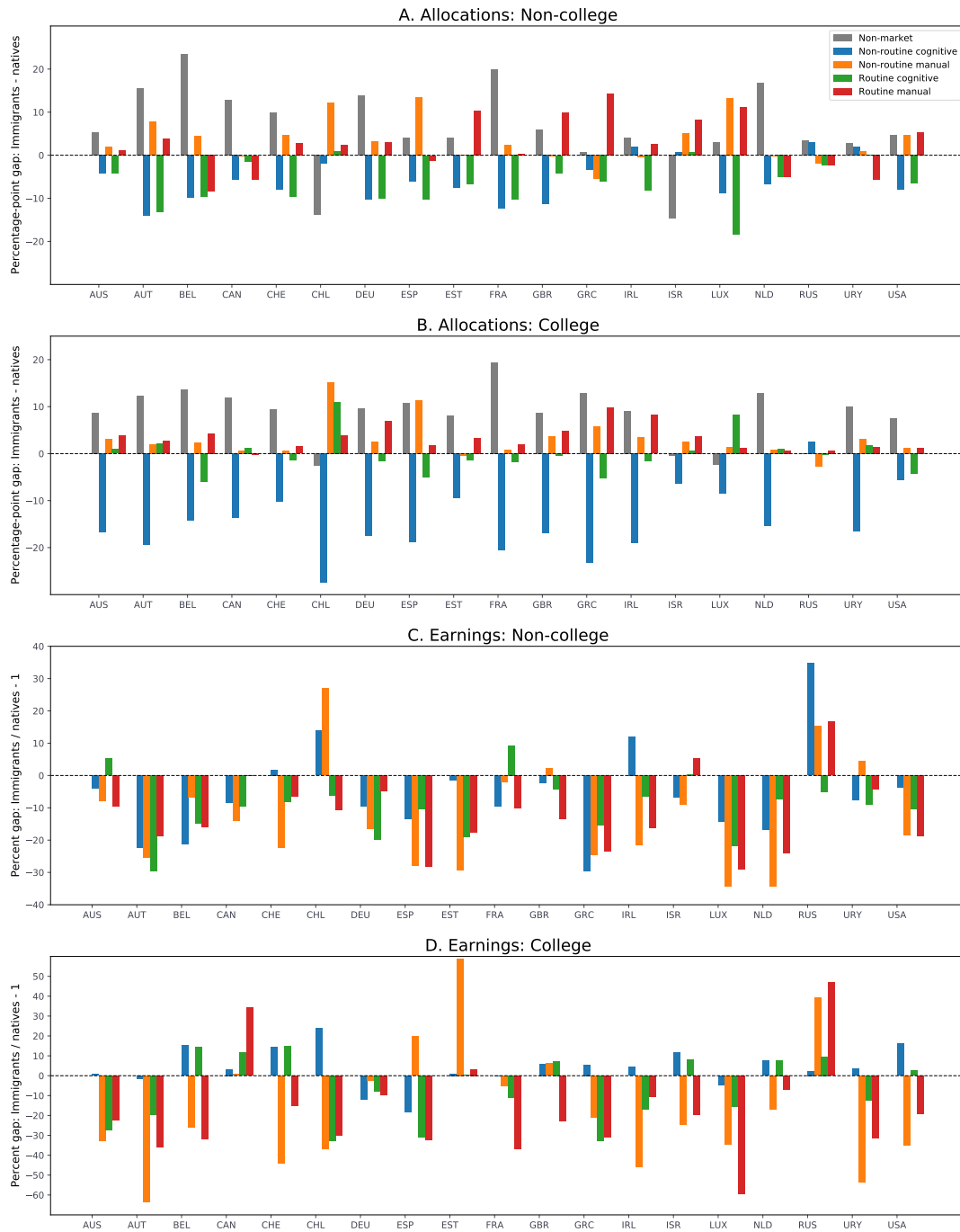
[3]These choices are broadly consistent with the one-digit occupation classifications using the SOC.

Figure A1: Allocations and earnings between immigrants and natives: Gender

A. Allocations: Male

B. Allocations: Female

C. Earnings: Male

D. Earnings: Female

Note: This figure presents differences by gender in labor market allocations and earnings between immigrants and natives across countries. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average labor earnings of immigrants and natives in each occupation. Panels A and B show the percentage-point gap (calculated as immigrants−natives) between fractions of immigrants and natives in each occupation across countries separately for males and females, respectively. Panels C and D show the percent gap (calculated as immigrants/natives − 1) between 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 LIS database.

Figure A2: Allocations and earnings between immigrants and natives: Education

A. Allocations: Non-college

B. Allocations: College

C. Earnings: Non-college
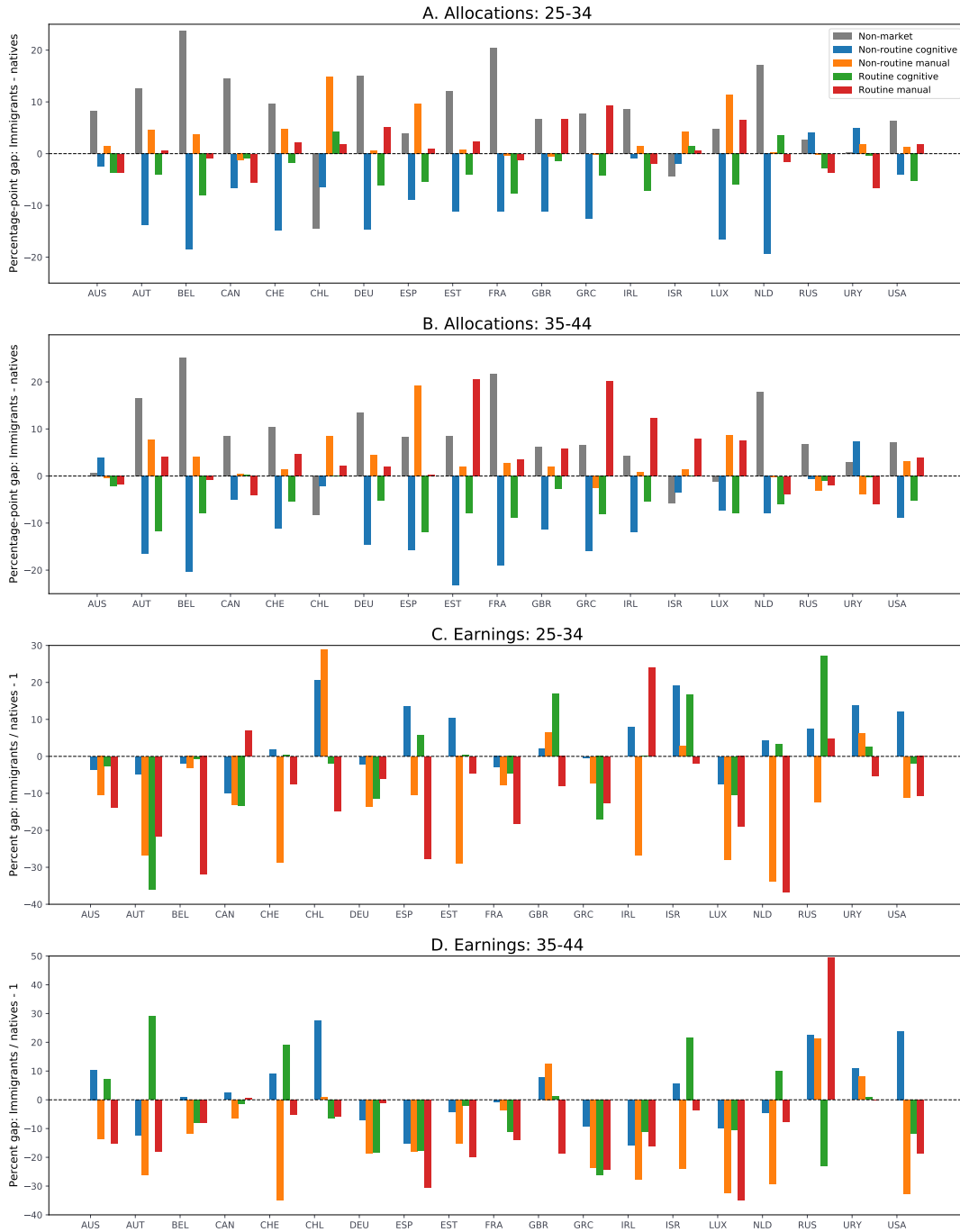
D. Earnings: College

Note: This figure presents differences by education in the labor market allocations and earnings between immigrants and natives across countries. For each country, we calculate the fraction of immigrants (natives) in each occupation among all immigrants (natives) as well as the average labor earnings of immigrants and natives in each occupation. Panels A and B show the percentage-point gap (calculated as immigrants − natives) between fractions of immigrants and natives in each occupation across countries separately for individuals without a college degree and with a college degree, respectively. Panels C and D show the percent gap (calculated as immigrants/natives − 1) between 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 LIS database.

Figure A3: 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 As and B show the percentage-point gap (calculated as immigrants − natives) between fractions of immigrants and natives in each occupation across countries separately for individuals of ages between 25 and 34 and 35 and 44, respectively. Panels C and D show the percent gap (calculated as immigrants/natives − 1) between 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 LIS database.

in around half of the countries in our sample. Finally, we also find that life-cycle effects impact the earnings gaps between immigrants and natives differently across countries. For instance, in the U.S., the average earnings of immigrants between ages 25 and 34 are larger in non-routine cognitive occupations than those of natives in the same age group. This gap widens further for individuals between ages 35 and 44. However, in Spain, immigrants between ages 25 and 34 also earn more than natives in this age group but this is no longer true for individuals between ages 35 and 44. These findings emphasize the importance of accounting for demographic differences between immigrants and natives across countries when estimating the model.

C   Estimation

In this appendix, we provide derivations of equations used in Section 3.3 and discuss details on the implementation of our estimation approach.

C.1   Identification

We now present the derivation of Equations (1)-(4) in the paper.

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

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

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

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

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

where γ_{em} is the Euler-Mascheroni constant.

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

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

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

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

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

$$n_{ig}^j = N_{ig} z_{ig} \left(p_{ig}^j\right)^{\frac{\eta-1}{\eta}} \Gamma\left(1 - \frac{1}{\eta}\right).$$

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

$$\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{ig}^k} = \frac{\left(1 - \tau_g^j - \kappa_{ig}^j\right) w_{ig}^j}{\left(1 - \tau_g^k - \kappa_{ig}^k\right) w_{ig}^k} \left(\frac{p_{ig}^k}{p_{ig}^j}\right)^{\frac{1}{\eta}}.$$

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

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

Equation 2 Our derivation of Equation (2) has two parts. Throughout the whole derivation, consider two worker (type, subtype) pairs (i, g) and (q, r) who choose a given occupation j.

The first part of the derivation begins by computing the ratio of geometric average earnings across these workers:

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

Now, plugging in the corresponding expressions for p_{ig}^j and p_{qr}^j and then rearranging, we obtain:

$$\frac{\sum_{\ell=0}^J \left[z_{qr}(1 + \gamma_{qr}^\ell)\nu_r^\ell \left(1 - \tau_r^\ell - \kappa_{qr}^\ell\right) w_{qr}^\ell\right]}{\sum_{\ell=0}^J \left[z_{ig}(1 + \gamma_{ig}^\ell)\nu_g^\ell \left(1 - \tau_g^\ell - \kappa_{ig}^\ell\right) w_{ig}^\ell\right]} = \frac{(1 + \gamma_{qr}^j)\nu_r^j}{(1 + \gamma_{ig}^j)\nu_g^j} \frac{\text{Earnings}_{qr}^j}{\text{Earnings}_{ig}^j}.$$

We use this expression in the second part of the derivation.

The second part of the derivation begins by computing the relative propensities to choose occupation j between worker (type, subtype) (i, g) and (q, r):

$$\frac{p_{ig}^j}{p_{qr}^j} = \left[\frac{(1 + \gamma_{ig}^j)\nu_g^j \left(1 - \tau_g^j - \kappa_{ig}^j\right) w_{ig}^j}{(1 + \gamma_{qr}^j)\nu_r^j \left(1 - \tau_r^j - \kappa_{qr}^j\right) w_{qr}^j}\right]^\eta \frac{\sum_{\ell=0}^J \left[(1 + \gamma_{qr}^\ell)\nu_r^\ell \left(1 - \tau_r^\ell - \kappa_{qr}^\ell\right) w_{qr}^\ell\right]^\eta}{\sum_{\ell=0}^J \left[(1 + \gamma_{ig}^\ell)\nu_g^\ell \left(1 - \tau_g^\ell - \kappa_{ig}^\ell\right) w_{ig}^\ell\right]^\eta}.$$

We plug the expression obtained into the first part of the derivation and then rearrange and simplify to obtain Equation (2):

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

Equation 3 Our derivation of Equation (3) also has two parts. Throughout the whole derivation, consider two outer nests v and v' in a given occupation j.

The first part of the derivation begin with the observation that, under perfect substitution in the inner nest, Equation (2) implies:

$$\frac{w_v^j}{w_{v'}^j} = \left(\frac{p_{ig}^j}{p_{qr}^j}\right)^{\frac{1}{\eta}} \frac{\left(1 - \tau_r^j - \kappa_{qr}^j\right)}{\left(1 - \tau_g^j - \kappa_{ig}^j\right)} \frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{qr}^j} \frac{z_{qr}}{z_{ig}}.$$

We use this expression in the second part of the derivation.

For the second part of the derivation, consider the relative demand for labor across the two outer nests v and v' in occupation j:

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

Plugging in the labor market clearing condition, we can simplify the expression to obtain:

$$\left(\frac{w_v^j}{w_{v'}^j}\right)^{-\sigma_j} = \left\{\frac{\sum_{i \in \mathcal{I}_v} \sum_{g=1}^G N_{ig} z_{ig} \left(p_{ig}^j\right)^{\frac{\eta-1}{\eta}}}{\sum_{i \in \mathcal{I}_{v'}} \sum_{g=1}^G N_{ig} z_{ig} \left(p_{ig}^j\right)^{\frac{\eta-1}{\eta}}}\right\}^{\frac{-1}{\sigma_j}}.$$

Now, replacing $\frac{w_v^j}{w_{v'}^j}$ with the expression obtained in the first part of the derivation and then rearranging the terms, we obtain Equation (3):

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

Equation 4 Consider now the relative demand for labor across market occupations j and k within outer nest v:

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

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

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

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

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

Now, plugging in the respective labor market clearing conditions, substituting the wage ratio using the first step of our derivation of Equation (1), normalizing $A_k=1$, and then simplifying, we obtain Equation (4):

$$A_j=\left\{\left[\left(\frac{p_{ig}^j}{p_{qr}^j}\right)^{\frac{1}{\eta}}\frac{(1-\tau_r^j-\kappa_{qr}^j)}{(1-\tau_g^j-\kappa_{ig}^j)}\frac{\text{Earnings}_{ig}^j}{\text{Earnings}_{qr}^j}\frac{z_{qr}}{z_{ig}}\right]^{\sigma}\frac{\sum_{i\in\mathcal{I}_v}\sum_{g=1}^{G}N_{ig}z_{ig}\left(p_{ig}^j\right)^{\frac{\eta-1}{\eta}}}{\sum_{i\in\mathcal{I}_v}\sum_{g=1}^{G}N_{ig}z_{ig}\left(p_{ig}^k\right)^{\frac{\eta-1}{\eta}}}\right\}^{\frac{1}{\sigma-1}}.$$

C.2 Implementation

Finally, we provide details on the implementation of our estimation approach. We estimate the parameters of the model following the discussion in Section 3.3. Recall that the derivations in Section 3.3 are based on the restriction that there is perfect substitution across individuals 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 labor bundles in the inner nest.

To estimate the model, we restrict attention to individual types and subtypes with at least one observation in a market occupation and at least one observation in the non-market occupation. Individual types and subtypes without observations in an occupation are considered under the following imputation: the share of such individuals in the missing occupation is assumed to be infinitesimal, and their earnings are assumed to be the average earnings across all observed market occupations for the given (type, subtype) pair. Our findings are robust to alternative ways to handling

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Table A2: Estimation results for distribution and earnings

Occupation type	Distribution						
	N	I_{0-10}	I_{10+}	$I_{Low\ Eng}$	$I_{High\ Eng}$	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
Non-market	0.26	0.32	0.26	0.43	0.25	0.26	0.26
	Earnings						
Occupation type	N	I_{0-10}	I_{10+}	$I_{Low\ Eng}$	$I_{High\ Eng}$	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

Note: This table presents model-implied targeted moments for the allocation of individual types across occupations. We first calculate the outcomes for each individual (type, subtype) pair in each occupation. For expositional purposes, we report the average moments for natives and immigrant types across all occupations. N denotes natives, I_{0-10} denotes recent immigrants ($\leq$ 10 years), I_{10+} denotes established immigrants (>10 years), $I_{Low\ Eng}$ denotes low English proficiency immigrants, $I_{High\ Eng}$ denotes high English proficiency immigrants, I_{LIC} denotes immigrants originating from low-income countries, and I_{HIC} denotes immigrants originating from high-income countries.

missing observations.

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

D Results

In this section, we provide additional results to complement some of our results in the main text.

Within-market reallocation effects of removing immigrant wedges In Section 4.2, we show that removing immigrant wedges leads to a small decline in aggregate TFP. This result is a byproduct of two counteracting forces: a decline in productivity due to an inflow of less-productive workers who switch from the non-market occupation to market occupations and an increase in productivity due to the reallocation of workers across market occupations. We now decompose the effects of the latter. To do so, we prevent movement of individuals in and out of the non-market occupation and only focus on the reallocation of individuals within market occupations when immigrant wedges are removed. Table A3 presents the results.

Table A3: Within market reallocation effects of removing immigrant wedges

| Occupation type | Percent change | | | Change in |
	Real GDP	TFP	Labor	immigrant share (pp)
Aggregate	0.31	0.31	0	0
Non-routine cognitive	1.12	-0.60	1.73	1.46
Non-routine manual	-4.24	2.73	-6.79	-5.44
Routine cognitive	4.13	-0.38	4.52	3.69
Routine manual	-2.15	1.15	-3.26	-2.59

Note: This table presents the percent change in aggregate and occupation-specific real GDP, TFP, and labor when we prevent inflows to and outflows from the non-market occupation upon removal of immigrant wedges to isolate the effects of within-market reallocation. 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 market occupations (or each occupation). The change in immigrant share denotes the percentage-point (pp) change in the fraction of immigrants employed in market occupations or each occupation.

We find that TFP increases by 0.31%, implying that the within-market reallocation of individuals leads to an improvement in aggregate productivity. While the magnitude of this improvement through within-market reallocation of individuals may seem small, this result depends on the underlying distributions of estimated immigrant wedges. In Section 6, we show that the gains from removing immigrant wedges are larger in countries where the estimated wedges are larger for more-productive occupations or individuals. Finally, focusing only on the within-market reallocation of individuals reveals interesting results across occupations. For example, productivity declines by much less in cognitive occupations when we prevent the movement from the non-market occupation to market occupations upon removing immigrant wedges compared to the scenario when we allow it. This is because, in the latter scenario, the inflow of relatively less-productive individuals from the non-market occupation to cognitive occupations amplifies the productivity losses in these occupations.

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

When evaluating the quantitative significance of our findings, we need to confront the observation that the aggregate effects of removing immigrant wedges are naturally a function of the share of immigrants in the economy. If immigrants are few, then mechanically the effects will be estimated to be modest even if the distortions are

Table A4: Gains from removing immigrant barriers vs. gains from immigration

	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	6.91		

Note: This table presents a comparison of real GDP, TFP, and labor under three scenarios: (i) if there are no immigrants in the economy, (ii) the baseline economy (the economy with immigrants and immigrant wedges), and (iii) the economy with immigrants but without immigrant wedges.

substantial. Thus, we put our findings in context by comparing the effects from removing immigrant wedges to the overall contribution of immigrants to the U.S. economy. We compute the contribution of immigrants in the U.S. by comparing the baseline model with a counterfactual economy without immigrants, which we solve by setting the mass of immigrants to zero.

Table A4 reports the value of real GDP, TFP, and labor relative to the baseline for three economies: the economy without immigrants, the baseline economy (the economy with immigrants and immigrant wedges), and the economy with immigrants but 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). This implies that the real GDP gains from removing immigrant wedges are 6.91% of the total gains from immigration (2.94/42.5). Hence, we conclude immigrants' current contribution to the U.S. economy would increase by 6.91% in the absence of immigrant wedges.

Removing immigrant wedges for each immigrant type/subtype Table 5 in Section 4.3 presents the gains associated with removing immigrant wedges faced by specific immigrant types or subtypes. In order to provide further intuition for the results in Table 5, Table A5 presents the percent change in the mass of immigrants across market and non-market occupations under selected counterfactual economies wherein immigrant distortions for a specific immigrant type or subtype is removed. For example, the first two rows pertain to changes in the distribution of male and female immigrants across occupations under an economy where distortions for male immigrants are removed. A discussion of the results presented in Table A5 is provided around Table 5 in the main text.

Table A5: Reallocation arising from removing wedges by immigrant type/subtype

Wedges removed	Mass of subtype (% change)	Non-routine cognitive	Non-routine manual	Routine cognitive	Routine manual	Non-market
By gender						
Male	Male	22.0	76.0	-24.8	-7.7	-53.2
	Female	-1.8	-10.9	3.7	1.8	2.8
Female	Male	-4.4	-16.0	5.3	2.5	8.8
	Female	68.0	116.3	-16.4	-19.2	-70.1
By degree						
Non-college	Non-college	112.8	115.6	-19.1	-8.0	-61.4
	STEM	-2.2	-14.3	12.7	8.2	8.7
	Law or medical	-2.7	-14.9	11.5	5.9	8.4
	Social sciences	-2.7	-14.7	11.9	6.7	8.0
STEM	Non-college	-1.0	-5.2	-0.5	0.1	2.4
	STEM	11.6	88.1	19.0	7.4	-77.9
	Law or medical	-0.6	-4.8	0.0	0.4	3.1
	Social sciences	-0.5	-4.7	0.1	0.7	3.0
Law or medical	Non-college	-0.7	-0.7	0.4	0.0	0.2
	STEM	-0.2	-0.2	0.9	0.5	0.7
	Law or medical	23.7	54.9	-47.3	-30.3	-75.7
	Social sciences	-0.3	-0.3	0.7	0.3	0.5
Social sciences	Non-college	-4.1	-5.6	1.0	1.2	1.7
	STEM	-1.4	-3.0	3.8	4.5	4.5
	Law or medical	-1.5	-3.3	3.5	3.5	4.5
	Social sciences	36.9	53.5	-26.4	-40.9	-81.1

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

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

Table A6 presents the gains from removing immigrant wedges by occupation. When immigrant wedges in a given occupation are removed, immigrants from other occupations (or the non-market occupation) are diverted toward this occupation. This implies that removing wedges to work in low-productivity occupations (e.g., non-

Table A6: Gains from removing immigrant wedges by occupation

Occupation	Real GDP (% change)	Share of population (baseline level, %)	Real GDP growth per 1% of imm. (%)
Non-routine cognitive	1.42	5.38	0.26
Non-routine manual	0.13	2.75	0.05
Routine cognitive	0.55	2.01	0.27
Routine manual	1.03	3.64	0.28

Note: This table presents the effects of removing immigrant wedges by occupation on real GDP. The first column presents the percent change in real GDP when immigrant wedges in a given occupation are removed relative to the baseline economy. The second column presents the share of immigrants in each occupation in the total population. Finally, the third column presents the ratio of real GDP growth (column 1) to the share of each occupation in the economy (column 2) to adjust for heterogeneity in the mass of individuals across occupations.

routine manual occupation, where occupation productivity A is estimated to be the lowest in Table 3) results in smaller increases of aggregate output, while the opposite is true for high-productivity occupations (e.g., non-routine cognitive occupation, where occupation productivity A is estimated to be the highest in Table 3). 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 for the other occupations in both absolute terms and per immigrant.

E   Robustness

In this section, we provide quantitative results on changes in aggregate real GDP, TFP, and labor when immigrant wedges are removed under the alternative specifications of our baseline model using the ACS, as mentioned throughout the text. In each of these specifications, we re-estimate the model's parameters and wedges and then compute changes in aggregate real GDP, TFP, and labor when immigrant wedges are removed. These results are summarized in Table A7. Overall, we show that these alternative specifications do not significantly alter our main conclusions.

First, in Section 3.1, when we partition market occupations into broad occupation categories, we consider four groups based on the skills and types of tasks involved, following Cortes, Jaimovich, Nekarda, and Siu (2020). In the ACS, this is achieved by using the SOC codes to assign each occupation into one of the four occupations. We choose this approach in our baseline exercise, as it simplifies the process of creating comparable occupation categories across countries when we move to our cross-country analysis in Section 6 using the LIS data. An alternative approach in the ACS is to create a task-intensity index for each occupation, following Autor and Dorn (2013).

Table A7: Gains from removing immigrant wedges under alternative specifications

	Percent change			Change in
	Real GDP	TFP	Labor	immigrant share (pp)
Baseline	2.94	-0.40	3.35	3.76
Autor and Dorn (2013) classification of occupations	3.13	-0.15	3.29	3.68
Hourly earnings as labor earnings	3.09	-0.15	3.25	3.72
25 percent UI replacement rate, $\lambda = 0.25$	3.09	-0.25	3.35	3.76
75 percent UI replacement rate, $\lambda = 0.75$	2.81	-0.53	3.35	3.76
Shape parameter of Frechet distribution $\eta = 2$	1.80	-0.92	2.74	2.53
Shape parameter of Frechet distribution $\eta = 6$	3.29	-0.23	3.52	4.53
Imperfect substitution between education groups	2.96	-0.49	3.48	3.85
Imperfect substitution across natives and all immigrant types	7.73	2.74	4.86	5.59
Elasticity across sectoral goods $\sigma = 1.65$	2.03	-0.25	2.29	4.57

Note: This table presents the percent changes in aggregate real GDP, TFP, and labor when immigrant wedges are removed under the baseline model and alternative specifications of the baseline model. Aggregate real GDP is output produced in market occupations, total factor productivity (TFP) is real GDP per worker, and labor is the mass of workers in market occupations. The change in immigrant share denotes the percentage-point change in the fraction of immigrants employed in market occupations. Please refer to main text for a detailed discussion on the alternative specifications of the baseline model.

When we instead use the Autor and Dorn (2013) classification of occupations, the decline in TFP when immigrant wedges are removed becomes smaller. Overall, the results remain roughly similar to our baseline results.

Second, we define labor earnings as total labor income in Section 3.1. Table A7 shows that, when we instead use hourly labor earnings, the results remain similar.

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

Fourth, in Section 3.2, we set the shape parameter of the Frechet distribution to $\eta = 4$. While this is a common value in the literature, we acknowledge that there are alternative values used across different studies. For this reason, we check the robustness of our main results under alternative values of η and find that they do not significantly affect our conclusions.

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

Sixth, in our model, we assume that the outer nest aggregates labor bundles of natives and all types of immigrants (without taking into account different immigrant types). Here, we make another change to the production technology so that the outer nest aggregates worker bundles of natives and all 18 types of immigrants (i.e., an aggregation across 19 worker bundles instead of 2 in the baseline specification). Recall that, in Section 3.3, we assume that labor bundles in the outer nest are imperfect substitutes, while labor bundles in the inner nest are perfect substitutes. Thus, the implication of this change in the production technology is that immigrants of different types now become imperfectly substitutable. This captures the possibility that immigrants with different characteristics based on time since arrival, fluency in English, and the income level of country of origin may be imperfectly substitutable. Table A7 shows that when these types of immigrants are imperfect substitutes, real GDP gains from removing wedges are significantly larger, a result that is primarily driven by positive TFP gains from removing wedges. This result is intuitive because, given that various immigrant types (such as recent immigrants and immigrants with low English proficiency) have much larger wedges across occupations, when these types are imperfectly substitutable with other immigrant types, the gains from removing wedges become much larger. This exercise shows that our baseline specification where all immigrant types are perfect substitutes sets a lower bar for gains from removing wedges. When all types of immigrants are imperfect substitutes, our framework predicts much larger gains from removing wedges.

Finally, in Section 3.2, following Burstein, Hanson, Tian, and Vogel (2020), we set the elasticity of substitution between natives and immigrants to $\sigma_j = 4.6 \ \forall j = 1, ..., J$. We also set the elasticity parameter across sectoral goods to $\sigma = 4.6$ to simplify the estimation, as $\sigma_j = \sigma \ \forall j = 1, ..., J$ allows us to analytically back out the model's parameters given the target moments. Here, we instead set $\sigma = 1.65$ as in Burstein, Hanson, Tian, and Vogel (2020). Given $\sigma \neq \sigma_j \ \forall j = 1, ..., J$, Equations (1)-(4) in the paper no longer hold exactly — yet, the model-implied moments still fit the target moments fairly well. In this case, we find that our main results remain similar.