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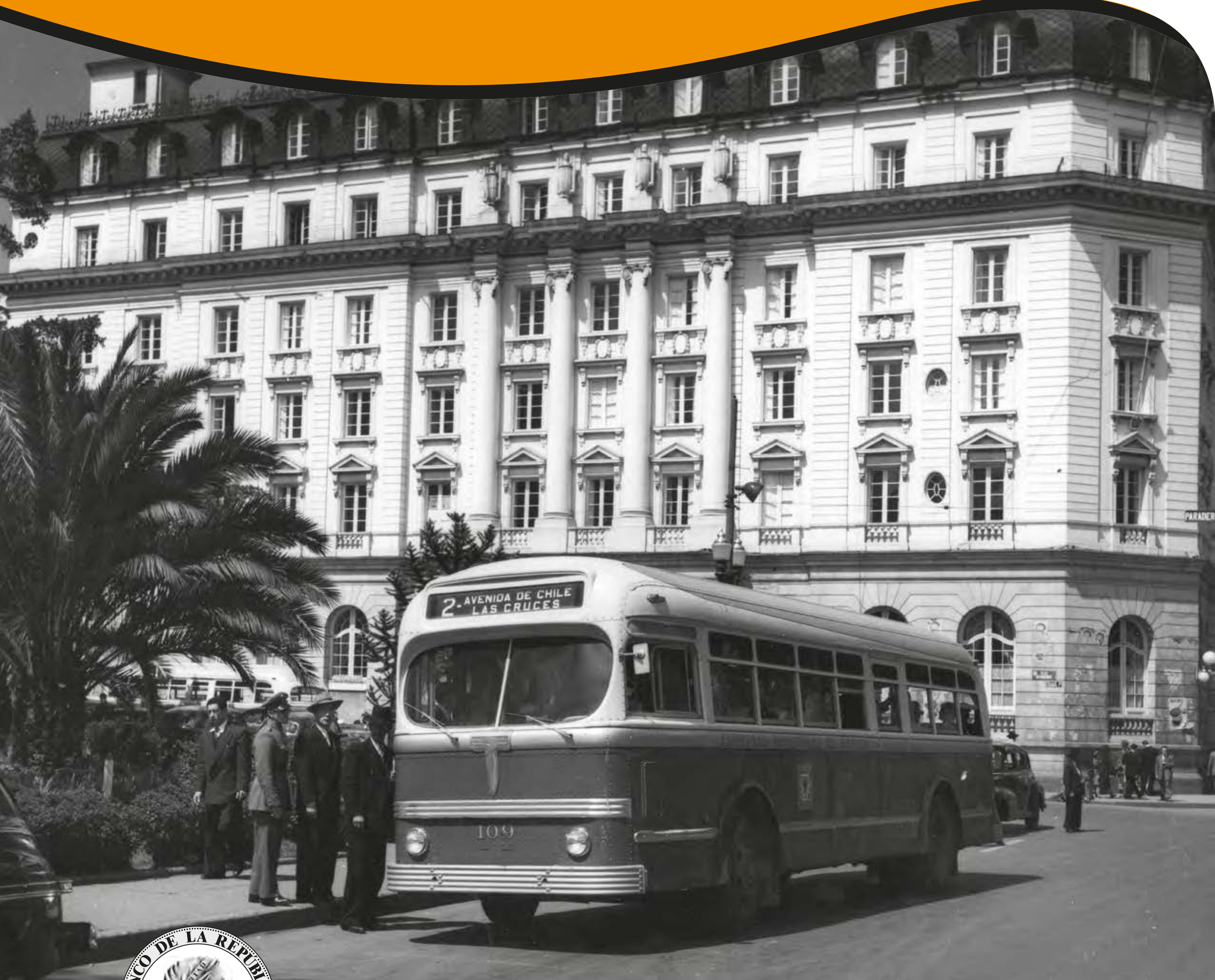

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Misallocation of the Immigrant Workforce: Aggregate Productivity Effects for the Host Country*

José Pulido† and Alejandra Varón‡

Abstract

Mass migrations can impact the amount of labor misallocation in the host country if immigrants, relative to natives, face more frictions that prevent them from working in their preferred occupations. The resulting misallocation would imply an aggregate productivity loss in the short run while migration occurs, but an subsequent lapse of productivity growth when the immigrants start to be assimilated by the labor market. We study the case of Colombia during 2015-2019, a period when the country received a massive inflow of migrants from Venezuela. Through the lens of a Roy model of occupational choice with two types of frictions - discrimination and barriers preventing workers from choosing their preferred occupations - we quantify the extent of occupational misallocation for immigrants, and its implications for Colombian aggregate labor productivity. Our estimates indicate that both type of frictions significatively misallocate Venezuelan immigrants. Removing those frictions would lead at least one third of immigrants to reallocate, permanently increasing Colombian aggregate productivity by 0.9%.

Keywords: Immigration, misallocation, Roy model, discrimination, productivity.
J.E.L. Classification: F22, O15, J61, O24.

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Asignación Ineficiente de la Fuerza Laboral Migrante: Efectos sobre la Productividad Agregada del País de Destino*

José Pulido† and Alejandra Varón‡

Resumen

Las migraciones masivas pueden aumentar la ineficiencia en la asignación del trabajo en el país anfitrión si los trabajadores inmigrantes, en relación con los nativos, enfrentan más fricciones en el mercado laboral que les impidan trabajar en sus ocupaciones deseadas. La mala asignación resultante genera una pérdida de productividad agregada en el corto plazo mientras la migración ocurre, pero un crecimiento posterior cuando los inmigrantes se asimilen en el mercado laboral. En este artículo estudiamos el caso de Colombia durante 2015-2019, un período en el que el país recibió una afluencia masiva de migrantes desde Venezuela. A partir de un modelo de Roy de elección ocupacional con dos tipos de fricciones – discriminación laboral y obstáculos que obligan a los trabajadores a elegir ocupaciones distintas a las de su preferencia – cuantificamos el grado de mala asignación del trabajo de los inmigrantes y sus implicaciones sobre la productividad agregada laboral colombiana. Nuestras estimaciones indican que ambos tipos de fricciones generan asignaciones ocupacionales ineficientes para los migrantes, y que al eliminar dichas fricciones al menos una tercera parte de los trabajadores migrantes cambiaria de ocupación, lo que incrementaría la productividad colombiana en un 0.9 % de forma permanente.

Palabras clave: Migración, asignación ocupacional, modelo de Roy, discriminación, productividad.
Clasificación J.E.L.: F22, O15, J61, O24.

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1 Introduction

Studies on the impacts of immigration on the host countries' labor markets have usually focused either on the process of immigrants assimilation or the possible displacement effects for natives workers.[1] An issue with macroeconomic implications that has been under-explored in the literature is the impact of immigrants on the destination country's aggregate productivity through their effect on the extent of misallocation in the labor market of the host country. If immigrants, relative to natives, face more frictions that prevent them from working in their preferred occupations, immigration might increase overall occupational misallocation, resulting in a loss of aggregate productivity due to the implied worsening of allocative efficiency.[2] In cases of massive immigration flows, this channel might generate sizable implications for the macroeconomic performance of the destination country.

The purpose of this paper is to assess whether this occupational misallocation is effectively larger for immigrants in a period of mass migration, and to derive its implications for the aggregate productivity of the host country. We study the case of Colombia during 2015-2019, a period when the country received a massive inflow of migrants from Venezuela, its main neighbor country. Over this time interval, the Latin America region witnessed an exodus of over 4.5 million Venezuelans, as a result of the country's economic and governance crisis. Neighboring Colombia was, by far, the main receptor of those migrants: By 2019, the country hosted around 2 millions of immigrants, leading to an important increase in its workforce, as high as 4.6%.

Using the Colombian household survey, we begin our study by documenting some facts that could suggest a greater amount of occupational misallocation for Venezuelan migrants relative to non-migrants. First, we show that although immigrants have on average more years of education than non-migrants, they tend to work in occupations with lower requirements of education relative to non-migrants.[3] Further, when we factor out differences in educational attainment and other observable characteristics, we find significant residual income gaps for immigrants. We show these gaps are the result of both a composition effect of observationally equivalent immigrants working more in occupations with lower remunerations relative to non-migrants, and of the presence of within-occupations gaps. In addition, the residual income-gaps are time-variant and positively correlated with the fraction of immigrants in the workforce.

[1] For an extensive literature review of the empirical studies until the the early 1990s see Borjas (1994); and for the empirical studies for more recent years, see Kerr and Kerr (2011).

[2] The literature on resource misallocation emphasizes that, given some amount of factors endowments, the micro-level misallocation of these factors across heterogeneous uses generates sizable losses in aggregate TFP. For an extensive review of this literature from the perspective of heterogeneous firms, see Restuccia and Rogerson (2013) or Hopenhayn (2014).

[3] This educational mismatch, where migrant workers are "overeducated" (i.e., their schooling level is greater than is typical for workers in each occupation) is commonly observed in the cases of high-skilled migration. For a summary of evidence, see McDonald and Worswick (2015) and Borjas, Chiswick and Elsner (2019).

Recent literature suggest that in a context where workers self-select into different sectors or occupations, residual-income gaps by themselves do not provide enough information about the presence of frictions or lack thereof (Hsieh et al., 2019; Pulido and Święcki, 2020). However, taken together, findings in earnings and occupational allocations can discipline a structural model to explore whether immigrants, relative to natives, might have been facing additional frictions preventing them from working in their preferred occupations. If true, the possibility that the massive inflow of Venezuelan migrants could impact Colombian aggregate productivity is not negligible. For this reason, we continue by guiding our analysis through the lens of a standard Roy's (1951) model of occupational choice. Within the model every worker is born with different draws of non-observable skills across occupations and are endowed with a certain amount of human capital, obtained before the period of migration. Each worker then chooses the occupation where she gets the highest indirect utility given her skills and human capital endowment.

We allow for two types of frictions that prevent migrant workers to choose their preferred occupations. First, we introduce pure discrimination in the labor market. Similar to Hsieh et al. (2019), discrimination takes the form of an occupation-specific wedge between marginal products and wages, a specification that is intended to capture the standard formulations of employer taste for discrimination in the literature (Becker, 1971; Altonji and Blank, 1999). Second, we allow that even after taking into account the implicit discrimination, immigrants are forced to make involuntary occupational choices in a different proportion than natives.[4] This could be consequence of additional potential obstacles that immigrants face to find a job in their desired occupations, including lack of professional connections or networks, issues with the recognition of educational degrees or difficulties to obtain permits to work legally. As in Pulido and Święcki (2020) we represent the extent of these barriers indirectly, by assuming that a fraction of workers in each period is forced to work in occupations other than the desired ones (randomly assigned), and by allowing these fractions to be different between native and immigrants workers.

We identify the extent of both types of frictions using the implications of our self-selection model for the occupational residual income gaps of immigrants. In the model, those gaps depend both on the relative occupational allocations of immigrants, reflecting how workers sort across occupations, and on the frictions each group of workers faces in the labor market. In this way, we are able to isolate the component of the immigrants' residual income gaps that only depends on frictions to assess how extensive those frictions are in the labor market. We find discriminatory wedges have a considerable dispersion among occupations, suggesting potential gains from reallocating workers across occupations when we remove those wedges. Further, we find that the proportions of immigrants in each period who are forced to make

[4] In our model, we use the word "natives" to refer to the group of non-migrants. But it is worth to mention that in the earlier years a significant proportion of immigrants were return migrants (born in Colombia).

involuntary choices tend to grow over time, coinciding with the rise in the immigration rate, increasing from 5% in 2015 to 9% in 2019. These values are larger than the obtained for native workers (4.7%).

Once our frictions are inferred, we conduct two counterfactual exercises to evaluate their quantitative importance. In the first, each set of frictions for immigrants is entirely removed. This a drastic reform in which all immigrants choose occupations according to their efficient allocation, an exercise that allows us to understand the relative importance of each set of frictions. We find that removing entirely both types of frictions would lead at least one third of immigrants to reallocate, and because it triggers general equilibrium effects, it also causes a small reallocation of natives, around 0.4% of their workforce. The reallocation of the entire workforce rises total output by as much as 0.9%, a result that is due to the increase in aggregate productivity by improving allocative efficiency among occupations. By decomposing the contribution of each type of frictions, we find that discrimination accounts for around two-thirds of the total gains from the extreme reform of eliminating all frictions, and involves stronger general equilibrium effects than the frictions that force workers to choose random allocations.

Our second counterfactual consists in equalizing immigrants' frictions to those inferred for natives. This reform provides a calculation of the aggregate productivity gains when immigrants are assimilated by the labor market, i.e. when they face the same extent of frictions than natives. By this way, this exercise offers a crude quantification of the aggregate implications of different programs that help immigrants to compete in the labor market under the same conditions than native workers, a valuable input from the viewpoint of policy analysis. Our results suggest that reducing immigrants frictions to a similar level to the inferred for natives would lead at least 9% of immigrants to reallocate, and as result, aggregate productivity would increase as much as 0.4%. Finally, we show that our macroeconomic gains from our counterfactual exercises are robust to non-trivial variations in the calibrated parameters and to alternative specifications of our model.

Related literature

Our paper contributes to the recent literature that quantitatively evaluates the role of misallocation of heterogeneous workers across sectors, locations or occupations in a context of self-selection (Lagakos and Waugh, 2013; Adamopoulos et al., 2017; Hsieh et al., 2019; Bryan and Morten, 2019; Pulido and Święcki, 2020). This quantification is usually tackle with a framework that encompasses a Roy's (1951) type model augmented by micro-level frictions. We apply this setting to study the extent of occupational misallocation of immigrants and its consequences on the host country's aggregate productivity, but our approach can be extended to study discrimination between more groups of workers, for example. Mainly, our specification borrows elements from the models used by Hsieh et al. (2019) and Pulido and Święcki (2020) for studying the allocation of all workers across occupations and sectors, respectively. As in these papers, we emphasize that reduced-form findings in income-gaps alone are not enough statistics to distinguish between sorting and misallocation. Hence, to make inferences about the extent of misallocation is necessary to nourish the empirical findings with the guidance of a structural model.

From the perspective of the migration literature, although the educational mismatch of immigrants to jobs within local labor markets in cases where migrants are more educated on average than natives is well documented (Chiswick and Miller, 2011; Nielsen, 2011; Joona, Gupta and Wadensjö, 2014; McDonald and Worswick, 2015; Borjas, Chiswick and Elsner, 2019), the exploration of the macroeconomic implications of this type of mismatch (or similar misallocations) has been less studied. Some recent studies address the consequences for aggregate efficiency of the degree of matching of immigrants and local firms. For example, using French matched employer-employee data, Orefice and Peri (2020) document that since immigrants have a larger dispersion on productivities, they increase the positive assortative matching between firms and workers. In the same vein, Burzynski and Gola (2019) illustrates that immigration may trigger a similar sorting mechanism in the host country using a model where two types of workers draw country-specific skills from different sets. Our paper contributes to this branch of literature using a different modeling approach. Instead of assuming immigrants are intrinsically different than natives because their skills are drawn from distributions with different attributes, we assume immigrants are misallocated due to the inherent frictions they face in the destination labor market. In the light of the Venezuelan migration to Colombia, where immigrants are culturally close to natives (both countries share a common language and demography and have similar average income and historical background, among other features), our approach seems to be more appropriate.

In broader terms, our paper aims to enrich the migration literature that explores macroeconomic effects in the host country beyond the usual short-term impacts on the labor market outcomes for natives. Particularly, we contribute to a body of work looking at the effects of immigration on aggregate productivity (Peri, 2012; Lewis, 2013; Hornung, 2014; Ortega and Peri, 2014; Aleksynska and Tritah, 2015). This literature usually highlights channels such as changes in the demographic composition of the workforce, shifts in firms' production functions, and the boost to innovation and total factor productivity growth; see Nathan (2014) for a review. Compared with these studies our research focus instead on a pure allocative mechanism, i.e. the way immigration shapes how total labor allocates across heterogeneous occupations, a channel that could also have sizable impacts on aggregate productivity, as the recent misallocation literature suggests.

Moreover, since a type of our differentiated frictions for immigrants can be rationalized as discriminatory preferences, our study also talks to the literature on discrimination for immigrants. Studies with evidence supporting the existence of such discrimination include Rydgren (2004) for Sweden, Oreopoulos (2011) for Canada, and Weichselbaumer (2017) for

Austria. One of the findings in this studies is that although statistical discrimination (due to stereotypical thinking) seems to contribute to the phenomenon, there is also an component that can be driven by employers' preferences against working with minority group members, the way we choose here to model discrimination.

Finally, this study belongs to a collection of recent papers which have used the Venezuelan exodus to assess its consequences for the Colombian economy: Rozo and Vargas (2018), Peñaloza (2019), Santamaria (2019), Caruso, Gomez Canon and Mueller (2019), Bonilla-Mejía et al. (2020), Knight and Tribín-Uribe (2020) and Bahar, Ibañez and Rozo (2020). With exception of Rozo and Vargas (2018) and Knight and Tribín-Uribe (2020), who explore electoral and crime outcomes respectively, the remaining works mainly investigate consequences of Venezuelan migration on the Colombian labor market, focusing on natives and immigrants wages, unemployment and participation rates. Their results, in line with the findings in the migration literature, show relatively minor displacement effects from immigration in terms of total earnings and employment for native workers; being the moderate effects mainly due to adjustments in the informal segment. Further, granting work permits to Venezuelan immigrants do not seem to have generated short run impacts on labor outcomes.

The organization of this paper is as follows. Section 2 presents our empirical motivation. Section 3 introduces our Roy model of occupational choice with two groups of workers and frictions for immigrants. Section 4 discusses the procedure that allows us to infer the magnitude of the frictions and presents our baseline results. Section 5 performs our counterfactual exercises of suppressing frictions for migrants, and equating them to those of native workers. We also evaluate some departures from the baseline model. Finally, section 6 concludes.

2 Empirical motivation and data

The roots of the "Venezuelan exodus" lay in the country's economic and political turmoil that began at the end of the presidency of Hugo Chávez and was exacerbated during the presidency of Nicolás Maduro. Both governments were characterized by the implementation of a series of socialist reforms that included economic policies such as land expropriations, nationalizations, price and currency controls and systematic restrictions on private businesses (Vera, 2015; Gutiérrez S., 2017). These policies, coupled with political mismanagement and an international outlook in 2014 with a downfall in oil prices (Venezuela's main export commodity), led the country to suffer by 2015 the worst economic crisis in its history.[5] The crisis was marked by hyperinflation and shortages of food and medicine and looting; that led to an escalation of starvation, disease, crime and mortality rates; a combination of factors that triggered Venezuelan migration (Mauricia, 2019; O'Neil, 2019).

According to the UN Refugee Agency (UNHCR) from 2015 to 2019 an estimated of 4.5

[5] And the worst facing a country that is not experiencing war since the mid-20th century (Kurmanaev, 2019).

million people fled Venezuela.[6] Colombia, Venezuela's main neighbor, was by far the main receptor of Venezuelan migrants. According to the Colombian household survey, where our data comes from (for a detailed description of our database see Appendix A.1), by 2019 the country hosted around 2 millions of Venezuelan immigrants.[7] For the Colombian labor market, with a size of around 23.6 million economically active population before the migration started, this massive inflow of migrants implied a significant expansion of the workforce. Figure 1 shows the inflow of Venezuelan immigrants and their participation in the workforce. Since 2015 immigrants' share in the workforce have steadily risen up, to reach 4.6% in 2019.

On average, Venezuelan migrants report more years of education than non-migrants, a pattern that was accentuated since 2017. Table A.1 in the Appendix displays some demographic characteristics (shares of males and average age and years of schooling) for migrants and non-migrants, both in the whole household survey and in our restricted sample, which includes only employees. Differences in average schooling years are evident in those two those samples but are even present only for adults 25 years and older (see Panel A of Figure 2), a comparison that aims to control for the age composition of the migrant population, which is more biased towards people in productive ages.

In spite of their higher educational attainment, Venezuelan migrants tend to work in occupations with lower requirements of skills relative to non-migrants. We consider the 30 most representative occupations in the survey (for a description of the occupations see Appendix A.2). Broadly speaking, the average years of education of workers in each occupation tends to decrease with the value of the occupation code: the first quintile of codes is related to high-skilled or "cognitive" occupations, whereas the fifth quintile is related to low-skill or "manual" occupations. Migrants have higher levels of education than no-migrants across most occupations (see Panel B of Figure 2), but, compared to non-migrants, their occupational allocation is more concentrated in the middle and the right side of the distribution, i.e. into occupations other than those with high skills requirements (Figure 3).

We also find there are important and significant residual (controlling for observables) income gaps for migrants. These gaps are estimated by using Mincerian regressions with the following general form:

$$lnY_{islt} = X_{it}\beta + \phi I_i + D_l + D_t + \varepsilon_{islt} \tag{1}$$

where Y_{islt} denotes a measure of labor income of individual i in occupation s, province l, and quarter t; X_{it} refers to a series of individual controls that include gender, work experience,

[6]Relative to other major migration waves seen in recent history, the magnitude of Venezuela's migration is only smaller than the originated by the Syrian war (5.6 million).

[7]It is worth to say that given the large amount of irregular migrant inflows, (i.e. immigrants without legal documentation), household surveys would offer a more accurate picture about the dimension of the phenomenon than records of the migration authorities. Nevertheless, a comparison of the estimates between both sources, in which migration authorities compute the amount of irregulars by imputation procedures, show similar magnitudes for the total migrants flows (Tribin-Uribe, 2020).

work experience squared and in most specifications years of education, plus an indicator of whether the household is in a rural area; D_l and D_t are province and time fixed effects; and I_i is an indicator of whether individual i is migrant, so ϕ captures the migrant premium of interest. Robust standard errors are clustered at the municipality level. Our preferred measure of labor income is one that includes both wages and fringe benefits for salaried workers, and net-profits from personal business in the case of non-salaried or self-employees.[8]

Columns (1)-(3) of Table 1 report the results from estimating equation (1) using our preferred measure of labor income. Before factoring out differences in educational attainment, column (1) shows that migrants on average perceive a residual labor income 39.8 log points [lp.] (or 49%) lower than non-migrants. Once we compare workers with similar years of education, column (2) shows that the premium decreases to 33.6 lp. (or 40%), a magnitude still considerable.[9]

A natural question is whether the latter premium is explained only by the different allocation of migrants across occupations, or whether non-migrants are also paid more in the same occupations. For this, column (3) of Table 1, reports the premium controlling for occupation fixed-effects. On average, the within-occupation premium is 21.7 lp., decreasing 12 lp. with respect to the premium without controlling for occupation fixed-effects. The fact that the within-occupation premium exists, but it is significatively lower than the premium in column (2), suggest us that both explanations play a role. Hence the income-gap for migrants is consequence not only of the composition effect of more migrants with similar observables working in occupations with lower remunerations relative to non-migrants, but also of the presence of within-occupations premia. Table 2 shows that these within-occupation premia, which are going to play a key role in identifying the magnitude of both frictions in our structural model, are heterogeneous across occupations and statistically significant (at 5% level or lower) in the case of 26 of our 30 occupations.

Two additional facts are worth noting. First, the reported income-gaps are not only the result of a different allocation of immigrants between the formal (salaried) and the informal (non-salaried) sector,[10] but also of the existence of intra-sectoral premia. For example, consider only the formal sector, where the labor income measure might be more accurate. Columns (4)-(6) of Table 1 use only salaried workers and shows that the reported premia remain and their magnitudes are even magnified in the formal sector. This result is not surprising since, in light

[8]Fringe benefits include extra-legal premiums, overtime pay, transportation subsidies, etc. Appendix A.3 depicts a brief summary of the different possible measures of labor income that can be obtained from the survey.

[9]Notice that although immigrants have on average more years of education, the premium in the residual income decreases when we control for education. This outcome is due to the composition of the migrants population across observables, effect that is absorbed by the whole set of controls. Without any control, the premium for migrants in total income is 27 lp., while controlling only for education is 5 lp. higher.

[10]In Colombia, in spite of the fact that the rate of informal work has decreased (at least until the end of 2019), informal workers still account in 2019 for almost half of the labor force.

of our findings, part of the income gaps are due to the additional frictions that immigrants face. Such barriers might be more pronounced in the formal sector, for example, in the case of the recognition of educational degrees, or the difficulties to obtain permits to work legally.

Second, the residual income-gaps are time-variant and are correlated with the magnitude of migration. Figure 4 shows the evolution of the migrant premium for each cross section in our data, and its 95% confidence interval. The residual income-gap is not statistically significant until the end of 2016. Starting in early 2017, and coinciding with the sudden increase in the migration inflows (Figure 1), the migrant premium becomes statistically significant and its magnitude begins to increase over time, to start to stabilize around 0.21 lp. in 2019. This temporal evolution suggests some correlation between the immigrants and the magnitude of their residual income-gaps.

Taken together, our findings point to the possibility that immigrants, relative to natives, might have been facing more barriers preventing them from working in their preferred occupations during our period of study. However, in a context with self-selection across occupations, the documented residual income-gaps by themselves do not provide enough evidence about the existence and the magnitude of the frictions. Consider for example the case of discrimination for immigrants in a given occupation, where the discrimination takes the form of a wedge between immigrant wages and their marginal productivities. Under self-selection, discrimination could deter migrant workers with low unobservable abilities to enter such occupation. Only immigrants with high enough abilities to overcome the discrimination hurdle will accept to work; a smaller fraction of the immigrant workforce relative to what would be without discrimination. Since the average quality of immigrants skills will be higher in this small fraction of their workforce, this composition effect could offset the direct effect of the discrimination wedge on the observed migrant premium. Therefore, we need to carefully consider the implications of self-selection for both immigrants' occupational allocations and their earnings gaps, in order to identify the existence and the nature of the frictions immigrants might face. The next section presents a Roy's (1951) type of model which purports to accomplish this objective.

3 Theoretical model

What can our reduced-form findings tell us about the extent of frictions that immigrants face? To answer this question we introduce in this section a simple discrete-time Roy model of occupational choice with two groups of workers (immigrants and natives[11]) and two types of frictions: discrimination and involuntary choices. We first present our model with no frictions. The frictionless economy resembles a particular case of Hsieh et al.'s (2019) general equilibrium model,[12] so we try to keep a similar notation for comparison. Next, we show how to generalize

[11]The word "natives" will refer to the group of non-migrants, but it is worth to mention that in the earlier years a significant proportion of immigrants from Venezuela were return migrants (born in Colombia).

[12]The case of a frictionless economy for a single-cohort with no heterogeneity in preferences.

this basic framework to introduce each type of our frictions.

3.1 Frictionless Economy

A continuum of workers choose an occupation i at each time t from a set of M available occupations, to maximize their contemporaneous utility.[13] There are two groups of workers: immigrants and natives, indexed by $g \in G = \{I, N\}$. Hence, workers can be characterized by the occupational choice i they make and the group g they belong. Workers are endowed by unobservable heterogeneous abilities ϵ_i over occupations, and possess an amount of human capital h_{igt} at time t that is given by:

$$h_{igt} = \overline{h}_{ig} a_{igt}^{\gamma} s_{ig}^{\phi_i} \tag{2}$$

where $\overline{h}_{ig}$ represents permanent differences in human capital or "talent" common to the group g in a given occupation i; γ captures the return to experience, a_{igt}, that we assume is simply the age of individual at time t minus 15 years; s_{ig} are the years of education, which we assume are fixed for all individuals prior to the migration period; and finally we let the returns to education to vary across occupations, with magnitude given by ϕ_i. Since both ages and years of education are observables, we collapse both variables in $x_{igt} \equiv a_{igt}^{\gamma} s_{ig}^{\phi_i}$, a term that we refer as the "returns" of observables.

For analytical tractability we borrow from Eaton and Kortum's (2002) model of trade and assume abilities draws ϵ_i are drown from a multivariate Fréchet distribution:

$$F(\epsilon_1, ..., \epsilon_M) = \exp\left[-\sum_{i}^{M} \epsilon_i^{-\theta}\right] \tag{3}$$

The parameter θ measures the dispersion of abilities of workers, with a higher value of θ corresponding to a smaller dispersion. The mean parameter of the Fréchet distribution is normalized to 1, but this parameter is isomorphic to $\overline{h}_{ig}$.

Denote y_{igt} the income that a worker receives for her labor supply at time t, equal to the value of her efficiency units of labor. This value is the product of the price per efficiency unit of labor in occupation i at time t, w_{it}, and the amount of efficiency units of labor, which in turn is the product of the worker's human capital, given by equation (2), and the worker's idiosyncratic talent ϵ in her chosen occupation i:

$$y_{igt} = w_{it} \epsilon_i \overline{h}_{ig} x_{igt} \tag{4}$$

For the formulation of workers' utility we allow for general societal preferences for specific occupations, similar to compensating differentials. Thus, workers contemporaneous utility U_{igt} is simply the product of their consumption at time t, c_{igt}, and a parameter z_{igt} that

[13] We abstract here from modeling inter-temporal choices given the short period of time we analyze and the lack of panel data to make inference. Turning the model into a dynamic one could greatly complicate the analysis without affecting our main insights.

measures the common utility benefit of all members of society from working in occupation i. For identification we normalize the value of this parameter to 1 in a given occupation so the values of z_{igt} are compensating differentials relative to the reference occupation. The worker's problem is thus to choose her occupation at the beginning of period t that maximizes her contemporaneous utility:

$$V_{igt} = \max_i \{U_{igt}\} = \max_i \{z_{igt} c_{igt}\}, \tag{5}$$

where in our static formulation consumption is simply equal to income, given by equation (4).

Finally, since our main interest is to study the effects of frictions for the allocation of heterogeneous workers across multiple occupations, we abstract from firm heterogeneity and instead assume that a representative firm produces final output Y from workers in M multiple occupations according to a CES technology:

$$Y_t = \left\{ \sum_i^M \left[A_{it} \sum_g^G q_{gt} p_{igt} \mathbb{E}\left(h_{igt}\epsilon_{ig}\right) \right]^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where A_{it} is the exogenous productivity of occupation i at time t, q_g is the total amount of workers in group g at time t, σ is the elasticity of substitution across occupations, p_{igt} is the share of workers of group g who choose occupation i at time t and $\mathbb{E}\left(h_{igt}\epsilon_{ig}\right)$ is a measure of the average quality of workers of group g who choose occupation i at time t. The latter two terms have an explicit solution given our functional form choice for the abilities draws ϵ_i, as we will show in Section 4. The competitive equilibrium of the model is shown in Appendix B.1.

3.2 Type I of frictions: Discrimination against immigrants

Our first case of frictions is discrimination against immigrants in the labor market. Similar to Hsieh et al. (2019), discrimination takes the form of an occupation-specific time-invariant wedge between immigrants's marginal products and their wages. This wedge can be derived as a function of discriminatory preferences of employers, following the literature on discrimination (Becker, 1971; Altonji and Blank, 1999). Assuming only immigrants face discrimination, workers' income in equation (4) becomes:

$$y_{igt} = \left(1 - \tau_{ig}\right) w_{it} \epsilon_i \overline{h}_{ig} x_{igt} \tag{7}$$

with $\tau_{ig} = 0$ if $g = N$. In this way, discrimination works as a "tax" on immigrants earnings, where the fraction of income taxed is equal to $\tau_i \in [0, 1]$. The fact that wedges are heterogeneous across occupations generate implications for selection of immigrants workers across occupations and their income gaps, as we will explain in section 4.

3.3 Type II of frictions: Involuntary occupation choices

The second type of frictions can be thought as barriers for immigrants that force some of them to work in occupations different to their preferred ones, even after taking into account the presence of discrimination that wedges imply. These frictions might reflect additional obstacles that immigrants face to find a job in their desired occupations, including lack of professional connections or networks, issues with the recognition of educational degrees or difficulties to obtain permits to work legally. We want to capture the idea that immigrants, relative to natives, have larger probabilities of not getting to work in the occupation they would like even if they have a strong comparative advantage in the occupation. In a richer setting, such type frictions could be rationalized by, for example, more unfavorable job search conditions for immigrants or higher search costs (Liu, 2010; Chassamboulli and Peri, 2015).

Following Pulido and Święcki (2020) we model the extent of these barriers indirectly by assuming that a fraction of workers are forced to make involuntary occupational choices, and by allowing this fraction to be possibly different between immigrants and natives. So we simply assume that at the beginning of each period every worker gets a random draw, such that a worker will be able to choose the occupation they desire with probability $1 - \alpha_g$, and they will be forced to work in any other occupation, selected randomly, with probability α_g. We allow for α_g to be time-variant for immigrants (so we will refer α_g as α_{gt}, keeping in mind $\alpha_{Nt} = \alpha_N \forall\ t$) to reflect the fact that this type of frictions could depend, for instance, on how sluggish their labor market is, which in turn would depend on the size of the immigration rate; or on the introduction of reforms that help to regularize immigrants.[14] The implications of α_{gt} for the allocations of immigrants across occupations and their income gaps over time are outlined in the next section.

4 Inference procedure

In this section we describe how the presence of both types of frictions for immigrants distort their occupational allocations and lead to income gaps, and hence how we can identify the extent of these frictions given data on income gaps and occupational shares for immigrants relative to natives. First, we present the implications of both types frictions for both occupational allocations and wage premia under our framework. Next, we describe our inference procedure to quantify the extent of frictions from data and comment on our baseline results.

4.1 Occupational shares and wage premia

Denote $\widetilde{w}_{igt} \equiv (1 - \tau_i)\, w_{it} \overline{h}_{ig} x_{igt} z_i$ the overall "reward" that someone from group g with the mean ability obtains by working in occupation i at time t, so the worker's problem at each

[14] For example, in August 2018 the Colombian Government introduced the PEP program, a large scale reform that regularized approximately half a million immigrants (Bahar, Ibañez and Rozo, 2020).

time t is to choose the occupation with the largest value of $\widetilde{w}_{igt}\epsilon_i$. Further, denote $\widetilde{p}_{igt}$ the share of workers of group g at time t that without forced choices, would choose occupation i. Proposition 1 refers to the occupational shares and the average ability of workers in each occupation.

Proposition 1. *The share of workers of group g who work in occupation i p_{igt} is given by:*

$$p_{igt} = (1 - \alpha_{gt})\, \widetilde{p}_{igt} + \alpha_{gt} M^{-1} \tag{8}$$

where $\widetilde{p}_{igt} = \frac{\widetilde{w}^{\theta}_{igt}}{\sum_s \widetilde{w}^{\theta}_{sgt}}$. Further, the geometric average of abilities of the group g in an occupation i at time t is given by:

$$\widehat{\epsilon} = \widetilde{\Gamma} \left(\frac{1}{\widetilde{p}_{igt}} \right)^{\frac{1}{\theta}(1-\delta_{igt})} \tag{9}$$

where $\widehat{x}$ denotes the geometric average, $\widehat{x} \equiv \exp^{\mathbb{E}(\log x)}$; $\delta_{igt} = \frac{\alpha_{gt}}{M p_{igt}}$ is the share of workers within an occupation i who do not voluntary chose such occupation; and $\widetilde{\Gamma} \equiv e^{\frac{\gamma_{em}}{\theta}}$, with γ_{em} the Euler–Mascheroni constant.

Proof. See Appendix B.2. □

Occupational shares of a group given in (8) are a weighted average between the random allocation of the fraction α_{gt} of workers who cannot make voluntary choices, and the allocation of the fraction $(1 - \alpha_{gt})$ of workers that can work in their preferred occupations, given by $\widetilde{p}_{igt}$. In turn, this latter allocation depends on the average reward $\widetilde{w}_{igt}$ relative to their power mean over all occupations ($\sum_s \widetilde{w}^{\theta}_{sgt}$). Thus, in the case in which all desired occupational choices were feasible ($\alpha_{gt} = 0\ \forall t$), occupational allocations would depend only on the relative returns of occupations, so the differences across allocations between natives and immigrants would come only from group-occupation specific factors. That is, the price per efficiency unit of labor in a given occupation (w_{it}), which is common between groups for each occupation, would not cause differences between immigrants' occupational shares relative to natives in a world with all desired choices are feasible. Only discrimination wedges, group-specific permanent differences in human capital and group-specific preferences for a given occupation, would cause differences in the allocations of immigrants. These forces as determinants of occupational allocations start to be distorted once involuntary choices are introduced, and lose explanatory power the larger is the extent of forced choices.

Self-selection induced by voluntary choices affects the average quality of workers in an occupation. To see this, notice that equation (9) implies that the geometric average of abilities in a given occupation is inversely related to the share of the group working in such occupation, p_{igt} (of which $\widetilde{p}_{igt}$ is direct function). Thus, in occupations where a group has low participation, for instance, because workers are discriminated against, workers will have higher abilities on average (in our example, because they are the ones who can overcome the discrimination hurdle). The presence of this sorting effect is stronger the larger are the allocations due to voluntary choices. In the extreme scenario where all choices were involuntary, $\alpha_{gt} = 1 \; \forall \; g, t$, this selection effect would not be present and their average ability would be the unconditional mean of the draws of abilities, given by $\widetilde{\Gamma}$ in the case of the Fréchet distribution.

The results for both occupational shares and average abilities in Proposition 1 lead to a direct implication in terms of the within-occupation income gaps for immigrants:

Corollary 1. *The income gap for immigrants in occupation i at time t (IG_{it}), defined as the ratio of the geometric average of earnings of immigrants relative to the same average for natives, is given by:*

$$IG_{it} \equiv \frac{\widehat{y}_{iIt}}{\widehat{y}_{iNt}} = (1 - \tau_{iI}) \frac{\overline{h}_{iI} \widehat{x}_{iIt} (\widetilde{p}_{iIt})^{\frac{1}{\theta}(\delta_{iIt} - 1)}}{\overline{h}_{iN} \widehat{x}_{iNt} (\widetilde{p}_{iNt})^{\frac{1}{\theta}(\delta_{iNt} - 1)}} \tag{10}$$

Proof. Straightforward from $\exp^{\mathbb{E}(y_{igt})} = (1 - \tau_{ig}) \, w_{it} \overline{h}_{ig} \exp^{\mathbb{E}[x_{igt} \log(\epsilon_i)]}$ and equations (8) and (9). □

Corollary 1 shows that occupational income gaps for immigrants are a combination of the effects of occupation-specific wedges, which reflect discriminatory frictions; gaps in returns on observables and in the permanent components of talent, reflecting the effect of differences in the composition of human capital across groups; and on the relative desired occupational allocations. These allocations are the result of sorting across occupations but are in turn distorted by the extent of frictions that force involuntary choices. Corollary 1 also implies that with information of within-occupations income gaps, occupational allocations, gaps in the "returns" of observables and an assumption about the latent permanent component of talent across groups for each occupation, it is possible to pin down the magnitudes of wedges $(1 - \tau_{ig})$ and probabilities of forced choices α_{gt} from the system of equations that (10) implies. This is the basic idea of our inference procedure, which is described below.

4.2 Inference procedure and results

Our procedure to quantify the extent of occupational misallocation for immigrants relies on finding the magnitudes of the frictions for which the system of equations (10) fits best the data. With an assumption about the innate differences of talent across groups in each occupation, $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$, a value for the parameter θ, and the definition of $\widetilde{p}_{igt}$ in equation (8), it is possible to find M wedges $(1 - \tau_{iI})$ and $T + 1$ probability of forced choices α_{It} and α_N for which the system of $M \times T$ equations (10) fits best our set of information $\{IG_{it}, p_{igt}, x_{igt}\}$.[15] Similar to

[15] Formally, defining the set of $M + T + 1$ variables $x = \{(1 - \tau_{iI}), \alpha_{It}, \alpha_N\}$ and the function $g(x)$ from $\mathbb{R}^{M+T+1}$ to $\mathbb{R}^{M \times T}$ given by $g(x) = IG_{it} - z_{it}(x)$ where $z_{it}(x)$ is the RHS of equation (10), since $M \times T > M + T + 1$ is not possible to find a exact solution of the overdetermined system of equations $g(x) = 0$. Instead, we solve the minimization problem $\min_x \parallel g(x) \parallel$, where $\parallel \cdot \parallel$ is a vector norm on $\boldsymbol{R}^{M+T+1}$ (we employ the Euclidean norm, i.e. least squares).

Hsieh et al. (2019), for our baseline results we assume that the levels of the latent permanent components are the same across groups and normalize them to 1 ($\overline{h}_{ig} = 1 \; \forall \; i, g$), so migrants have on average the same permanent components of talent than natives in each occupation,[16] but in our robustness checks we present alternatives to this assumption, modifying our model specification to infer values of $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ for each i.

We use data of immigrant and native workers between the ages of 25 and 70 for the period 2015 to 2019, so our inference focuses on workers after they finish schooling but prior to their retirement. In our baseline results we use our preferred measure of labor income converted to constant Colombian pesos of 2015. The occupational income gaps are defined as in equation (10), that is, in terms of geometric averages, but our results are similar if we use instead medians to avoid the influence of outliers. To measure the returns on observables x_{igt}, we need also values for the parameters γ and ϕ_i, the returns of experience and education respectively. For these values, we use the Mincerian returns in our pooled data from regressions of log income on years of schooling and age controlling for other observables.[17] For θ, the dispersion of abilities draws, similar to Hsieh et al. (2019) and Bryan and Morten (2019), we use the model's implication for the relative dispersion of wages within occupation-groups. Particularly, those wages should follow a Fréchet distribution with shape parameter equal to θ, and hence a ratio variance to mean equal to:

$$\frac{Variance\,(\theta)}{Mean\,(\theta)} = \frac{\Gamma\left(1-\frac{2}{\theta}\right) - \left[\Gamma\left(1-\frac{1}{\theta}\right)\right]^2}{\Gamma\left(1-\frac{1}{\theta}\right)} \tag{11}$$

for values of $\theta > 2$, where $\Gamma(\cdot)$ is the gamma function. So for each year, we compute the ratio variance to mean of the exponent of the residuals from cross-sectional regressions of log income on the 30×2 occupation-group dummies, and then solve equation (11) for the value of θ. The ratios variance to mean fluctuate between 2.43 and 2.55, so the resulting estimates of θ are on average 2.35. We use this value for θ in our baseline results, but we will explore robustness to setting it as low as 1.5 or as high as 3.5 in the next section. With this parametrization, we solve the system of equations resulting from inserting (8) in (10) using global solvers.[18]

Panel A of Table 3 shows our baseline results for both the variance of the estimated wedges and the probabilities of forced occupational choices, along with the values of the parameters used in the inference procedure. First, regarding wedges, it is worth to say that we focus on the

[16] In other words, we are assuming that there are no innate talent differences between natives and immigrants. Remember that $\overline{h}_{ig}$ is isomorphic to the mean parameter of the Fréchet distribution, so in our baseline both groups draw from the same distribution of abilities, a reasonable assumption.

[17] We use the same set of controls than in equation (1). For estimating γ, homogenous across occupations, we control also for occupation-group fixed effects. For estimating ϕ_i, heterogenous across occupations, we run the Mincerian regressions for each occupation.

[18] Particularly, we use the genetic algorithm with a population size of 2000 individuals, 10 times larger than the suggested by default in Matlab, for example. We verified that independently the initial population chosen, we get always the same solution.

variance of wedges because their dispersion is what really matters for workers misallocation;[19] their mean simply reflects the normalization used for the latent permanent component of talent across groups. We obtain a variance of 0.10, which implies a considerable dispersion of our estimated wedges: their values fluctuate between 0.3 times the median wedge (in the case of teaching professionals and scientists) and 1.7 times the median wedge (in the case of health professionals). Panel A of Figure 5 displays the estimated wedges in each occupation. The substantial heterogeneity of those values across occupations suggests that the gains from removing discrimination could be sizable.

Second, regarding the fractions of immigrants in each period who are forced to make involuntary choices, α_{It}, we find these fractions tend to grow over time, coinciding with the increase of the immigration rate, rising from 5.1% in 2015 to 9.2% in 2019. Panel B of Figure 5 displays these shares compared to the obtained value for native workers (α_N, equal to 4.7%). With exception of 2016, in all years of the Venezuelan exodus the proportions of immigrants making involuntary occupation choices are larger than the obtained for natives. By 2019, year of the largest migration inflows, this proportion is about twice as large as the one found for natives. Finally, Figure 6 plots the observed occupational income gaps compared to the predicted by our two set of estimated frictions using the RHS of equation (10), as a graphic representation of the fit of the model. For the relatively small number of parameters inferred, there is a strong positive association between the observed and predicted income gaps, with a relatively high correlation coefficient (0.73).

The magnitudes found for both types of frictions point in the direction that reallocating workers across occupations according to their frictionless choices could imply non-negligible gains on aggregate productivity. To quantify these gains, we first need to solve for the values of the remaining unobservable variables compatible with general equilibrium, and use those values to obtain the responses of the endogenous outcomes (allocations, prices and output) in the counterfactual equilibria. The next section develops a procedure in this direction and presents a series of robustness checks of the results.

5 Counterfactuals and robustness

In this section we show how aggregate productivity and occupational allocations would change when implementing two types of reforms: i) Removing entirely each type of frictions for immigrants; ii) Equalizing immigrants' frictions to those found for natives. We first describe the procedure to obtain those counterfactual equilibria and report its results. Next, we examine how sensitive are our results to the values of the calibrated parameters during the procedure, particularly to θ and σ. Finally, we explore robustness when we change the specification of

[19]If wedges were distributed log-normal along productivities, there would be a perfect correlation between the magnitude of the variance of wedges and the gains of reallocate workers across occupations; see Hsieh et al. (2019) for a proof, or in the context of firm-level misallocation, Chen and Irarrazabal (2015).

the model in order to infer differences in innate talent across occupations and to allow for time-variant discriminatory wedges.

5.1 Counterfactual exercises

To quantify the aggregate implications of our estimated frictions, we need first to solve for the remaining exogenous variables of the model: group-specific preferences for a given occupation, z_{igt}, and the productivities for the representative firm of each occupation i, A_{it}. These variables are kept constant when our counterfactual exercises are performed. Appendix B.3 depicts the procedure to solve for these values in the observed economy jointly with the equilibrium values of the endogenous efficiency wages (w_{it}) and the total output of the economy (Y_t), following several implications of the model. The procedure needs a value of σ, the elasticity of substitution among occupations, a parameter that we make equal to 3 in our baseline results (a common value in the literature). Nevertheless, we explore robustness to setting it as low as 2 or as high as 5 in the next subsection. Figure C.3 in Appendix C displays the resulting average values over years of group-specific preferences and productivities for each occupation. Preferences among occupations do not vary importantly between natives and immigrants, and, as expected, occupations with higher requirements of educational attainment are inferred as more productive for the representative firm.

Once this set of values are found for the observed equilibrium, two counterfactual equilibria can be computed. The first is to remove entirely each set of frictions for immigrants. In terms of our model, it involves to set τ_{iI} and α_{It} equal to zero, and derive the endogenous response of allocations, efficiency wages and total output in the new equilibria. This is a drastic reform in which all immigrants choose occupations according to the efficient allocation. Even though this counterfactual is extreme by nature, and hence perhaps unrealistic as policy reform, by removing jointly and separately each set of frictions we get a clear understanding of the relative importance of each one. The second counterfactual is equalizing immigrants' frictions to those found for natives. In spite of our inference procedure is able to tell us the extent of type II frictions for natives (α_N), one of its identification assumptions is that natives do not face "taxes" in their income. Hence, from our baseline results we cannot directly assess to which counterfactual value of wedges' variance we should reduce our estimated variance. So for this case, we propose a measure of the counterfactual variance of wedges based on estimating a restricted version of the model for different sub-groups of natives.

The procedure to obtain the endogenous variables in the counterfactuals once we have the intended values of frictions for each reform is described in detail in Appendix B.4. Basically, we use a fixed-point algorithm to find total output, occupational allocations and efficiency wages that clear each occupational labor market in each year given the values of the exogenous variables and the intended frictions in the proposed counterfactuals. The annual aggregate gains from the reforms are computed as the percentage change in total output for each year of the counterfactual economy relative to total output in the actual economy. In what follows, we describe our findings for each proposed reform.

Reform I: Removing frictions for immigrants

We first evaluate the counterfactual of removing entirely both types of frictions for immigrants ($\tau_{iI} = \alpha_{I,t} = 0 \; \forall \; i, t$). First rows of Panel B in Table 3 display the results for our baseline parametrization in each year of the studied period. By considering the results for the most recent year (2019), when the participation of immigrants in the Colombian workforce reaches its peak, removing all frictions for immigrants would permanently increase total output by as much as 0.9%. Since in both the counterfactual and the actual economy the amount of workers is the same, the rise in output is the result of the increase in aggregate labor productivity (where labor is measured in efficiency units) due to the improvement in the allocative efficiency of labor among occupations. An inspection of the counterfactual occupational allocation reveals that around 30% of immigrants in each year would reallocate as a consequence of the reform. This magnitude is a lower bound, since we are not able to quantify transitions that do not alter occupational shares.[20] The average counterfactual occupational allocation of immigrants compared to the observed one is displayed in Panel A of Figure 7, where it is evident that immigrants gain participation in occupations with higher skill requirements. Since the reallocation of immigrants workers has general equilibrium implications for efficiency wages, there is also a small response in terms of reallocation of natives: up to 0.4% of their workforce in 2019.[21]

Which type of friction is more important for these results? We next evaluate the counterfactuals of removing each type of frictions separately. By 2019, removing only discriminatory wedges ($\tau_{iI} = 0 \; \forall \; i$) leads 28% of immigrants and 0.4% of natives to reallocate, increasing aggregate productivity by 0.6%. So discriminatory wedges account for around two-thirds of the total gains from the reform of eliminating all frictions. Instead, removing only involuntary occupational choices ($\alpha_{It} = 0 \; \forall \; t$) leads only to 4% of immigrants to reallocate and increases aggregate productivity around 0.2%. As opposite to discriminatory wedges, immigrants who are misallocated by forced choices are randomly assigned among all occupations. Thus, their reallocation does not importantly affect efficiency wages, generating almost no changes in the allocation of natives. To sum up, discriminatory wedges have larger implications in terms of allocative efficiency and involve additional general equilibrium effects, a channel that has a second-round effect in the occupational allocation of the native workforce.

[20] The estimated reallocation and the following ones, are computed adding up the total amount of workers in occupations with positive variations in their participation in the total. So we are omitting possible reallocations that do not alter occupational shares (for example, a worker transitioning from sector s and s', whereas another worker makes the opposite transition) which we cannot identify.

[21] Panel B of Figure 7 shows for natives their counterfactual occupational allocation compared to the observed one, but the changes are very small.

Reform II: Equalizing immigrants' frictions to those found for natives

The aim of our second reform is to reduce frictions for immigrants to a similar level to that for natives. From the point of view of policy analysis, this counterfactual is perhaps more interesting because it provides a calculation of the aggregate productivity gains when immigrants are completely assimilated by the labor market of the host country and face the same frictions as natives. It also provides a crude quantification of the macroeconomic benefits of different programs that help to regularize and to reduce barriers for immigrants, allowing them to compete in the labor market under the same conditions than native workers.

For this counterfactual, we first equalize the values of the fractions of immigrants that are forced to make involuntary choices to the value estimated for natives, i.e. $\alpha_{It} = \alpha_N \; \forall \, t$. Second, we reduce the variance of our discriminatory wedges to a level that reflects the prevalent discrimination in the labor market of natives. Here we face the difficulty that one of our identification assumptions was that natives does not face "taxes" in their income, so their wages reflect their marginal productivities, and thus, from our results we do not have a direct measure of the prevalent discrimination in the labor market for natives.[22] In order to gauge the extent of this discrimination, we re-estimate our model for sub-groups of natives for which one could presumably argue there would be discrimination against them, constraining α_{gt} to our intended value α_N. This out-of-the model inference, although not perfect, will offer us an approximate value of the variance of the wedges for our counterfactual.

For this exercise, we choose as the possible groups facing discrimination women and rural workers. So we re-estimate the constrained model only for native workers using the following four subpopulations: urban-men (UM), rural-men (RM), urban-women (UW), and rural-women (RW). For identification, we assume UM do not face discrimination. With our baseline parametrization, we obtain a variance of wedges equal to 0.03 for RM, 0.08 for UW and 0.10 for WR; a ranking that seems reasonable. Using the average shares of the four groups in the total native population, our computed variances imply a pooled variance of 0.047. This value is close to the obtained in the case of estimating the restricted model only for men and women with women facing discrimination (0.044), or only for urban and rural workers with rural workers facing discrimination (0.040).[23] Therefore, in our counterfactual we shrink immigrants wedges until they exhibit a variance equal to 0.047, which corresponds to 47% of our estimated value of 0.100.

Panel C in Table 3 displays the results for our baseline parametrization. By 2019, reducing immigrants frictions to a similar level to the inferred for natives would lead 9.1% of immigrants and 0.1% of natives to reallocate. Figure 8 shows for each group the average counterfactual

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[22] This assumption was needed because from the system of equations (10) , $(1 - \tau_{iI})$ would be indistinguishable from $\frac{(1-\tau_{iI})}{(1-\tau_{iN})}$ if we would have assumed wedges for natives too.

[23] We also estimate a placebo test in which we divide the natives' population into two random groups, to verify that our inference was effectively capturing some type of discrimination instead of measurement error, for instance. In this case, we estimate a variance equal to 0.001.

occupational allocations, distributions that are half-way between the observed and the counterfactuals with the first reform. As result, Colombian aggregate labor productivity would permanently increase up to 0.4% due to the assimilation of the new workforce. At this point it is worth to say that it is a stylized fact that processes of immigrants' assimilation usually take several years to occur,[24] so in reality the new level of output would be reached gradually over several years.

5.2 Robustness to parametrization

We now explore robustness of our baseline results to alternate values of our calibrated parameters θ and σ. Consider first robustness to changes in the Fréchet shape parameter θ. This parameter is inversely related to the dispersion of abilities draws, and, contrary to σ, affects the values of the estimated frictions. Thus, θ has both a direct and an indirect effect on the aggregate gains of our reforms. The former effect refers to the impact of θ for a given value of our estimated frictions. Since the elasticity of total output to the efficiency loss caused by the variance of wedges is a direct function of θ,[25] the direct effect implies that the loss in aggregate productivity conditional to the extent of the frictions is increasing in θ. Instead, the indirect effect refers to the impact of θ on the aggregate gains via the estimated frictions, particularly the variance of wedges. For a given value of involuntary choices, a larger dispersion of abilities draws (smaller values of θ) implies individuals have stronger patterns of comparative advantage across sectors, so in order to rationalize the observed occupational income gaps and allocations more discrimination is needed. By this channel, the variance of wedges, and in turn the aggregate gains of reforms, are thus decreasing in θ. This indirect effect can be attenuated if θ also affects the values obtained for the fractions of involuntary choices.

Columns (2) and (3) of Table 4 show the values for the new estimated frictions and how our counterfactual results for 2019 change when we consider $\theta = 1.5$ and $\theta = 3.5$ respectively; while column (1) redisplays our baseline results from Table 3 for comparison.[26] By implementing Reform I in 2019, aggregate labor productivity gains rise from 0.73% with $\theta = 1.5$, to 0.90% with our baseline $\theta = 2.35$, and to 0.94% with $\theta = 3.5$. Similarly, the gains from Reform II increase from 0.30% with $\theta = 1.5$, to 0.38% with our baseline $\theta = 2.35$, and to 0.46% with $\theta = 3.5$. Hence, aggregate productivity gains from both reforms are increasing in θ, suggesting that the direct effect of θ is stronger that the indirect effect. However, it is worth to highlight

[24]For example, Kerr and Kerr (2011) document that, for the US, empirical studies find immigrants converge to natives' levels in around 10 years in terms of occupation rates, and in 15 years in terms of wages.

[25]Analytically, this can be shown by assuming a functional form for the joint distribution of productivities and wedges in order to obtain a closed-form expression for aggregate output in terms of the variance of wedges. For example, Hsieh et al. (2019) show that, abstracting from involuntary choices and assuming a joint log-normal distribution and $\sigma \to \infty$, such elasticity is equal to $\frac{1}{2}(\theta - 1)$. Otherwise, only by numerical simulations this could be exemplified.

[26]For the remaining years, a comparison of the time series of the aggregate gains of each reform is displayed in Figure C.1 in Appendix C

that this latter effect is present, anyway: the procedure infers a larger variance of wedges when θ decreases to 1.5.[27] Overall, our estimated gains from removing immigrants frictions exhibit only a moderate sensitivity to changes in θ, so our conclusions are not very affected by the calibration of θ.

Now consider robustness to changes in the elasticity of substitution σ between occupations. Columns (4) and (5) of Table 4 return to our baseline $\theta = 2.35$ and vary σ, from $\sigma = 2$ in Column (4) to $\sigma = 5$ in Column (5). Since σ does not have any role in the estimation of frictions, the magnitudes of the inferred frictions in both cases are equal to those in our baseline parametrization. However, the same values for frictions have slightly different implications for aggregate labor productivity. Gains from Reform I increase from 0.84% with $\sigma = 2$ to 0.96% with $\sigma = 5$, whereas gains from Reform II rise from 0.36% with $\sigma = 2$ to 0.39% with $\sigma = 5$, so the changes in the gains are marginal. Intuitively, the result that aggregate productivity gains are increasing in σ reflects the fact that with more substitutability across occupations the labor demands for an occupation-group are more sensitive to frictions, and the firm is thus more prone to use misallocated labor, increasing the efficiency loss. To sum up, the gains from our reforms are not very affected by changes in σ, suggesting us that our results are also not very affected by the calibration of σ.

5.3 Robustness to specification

Finally we explore robustness to two different model specifications. The first aims to infer simultaneously values for $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$. One of our identifying assumptions is that there are no innate talent differences between natives and immigrants, i.e. $\overline{h}_{ig} = 1$. This assumption was needed because from the system of equations (10), $(1 - \tau_{iI})$ would be indistinguishable from $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ if we would have assumed differences in the permanent component of talent between groups. An alternative specification of the model that allows us to infer values of $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ is to assume that discrimination has not always been present for immigrants, but only when their presence was very noticeable to the public. So we choose an arbitrary threshold for the immigration rate (1%) from which the wedges begin to appear.[28] This means that only from 2017 onwards we assume immigrants face discriminatory wedges. Hence, before 2017, their observed income gaps corrected for selection effects and returns on observables are only consequence of differences in innate talent, whereas from 2017 onwards are consequence both from differences in innate talent and discrimination.

Column (2) in Table 5 shows the estimated frictions and the results for reforms in 2019 for this specification, while Column (1) of the table redisplays our baseline estimates from

[27]When θ increases to 3.5, there is almost no change in the variance of wedges. This is because the procedure also infers a simultaneous increase in the extent of involuntary frictions. If we would have restricted the procedure to the same values of α_{gt} than in the baseline, we would have obtained a variance equal to 0.073.

[28]Results are similar choosing one year after or before the selected year.

Table 3 for comparison.[29] With respect to our baseline, the inferred variance of the wedges increases from 0.100 to 0.162, while the extent of type II frictions for immigrants marginally decreases in all years. For natives, instead, the proportion of involuntary choices strongly decreases from 4.7% in the baseline to 0.7%. Figure C.4 in Appendix C shows the inferred values for the relative innate talent differences, which, in spite of exhibiting some heterogeneity across occupations, are on average very close to one (0.97), providing some support for the assumption in our baseline. The presence of differences in innate talent across occupations not only helps the model to have a better fit to the data (see Panel A of Figure C.5 in Appendix C, in which the correlation coefficient between the observed and predicted income gaps is 0.87), a non-surprising result given the lower parsimony of this specification; but also decreases the power of discriminatory wedges to explain the observed income gaps. Hence, even though discriminatory wedges have a larger variance than in our baseline, removing entirely those wedges have a smaller impact on aggregate productivity. Total gains from Reform I decrease from 0.90% in our baseline to 0.52%, a result that is due to the smaller contribution of removing only wedges: while removing only involuntary choices leads to similar gains (0.21%) than in our baseline (0.23%), removing only wedges imply gains of only 0.29%, compared to 0.63% in our baseline. But for Reform II, the consequences for aggregate productivity are pretty similar.[30] This is because the smaller gains from shrinking wedges are compensated with larger gains from equating α_{It} to α_N, given that α_N is now inferred lower. Aggregate gains from Reform II are now 0.31%, close to our baseline (0.38%). To sum up, this specification has non-negligible effects for the gains from Reform I, but delivers similar results for the gains from Reform II.

Our second alternative specification allows us to consider time-variant discriminatory wedges. So we return to our assumption $\overline{h}_{ig} = 1$ and infer $(1 - \tau_{iIt})\ \forall\ i, t$. Here we face the difficulty that the system in (10) has $M \times T$ equations, and, with $M \times T$ wedges to infer, we must remove type II frictions to prevent the system from being underdetermined. By doing so, the system becomes exactly determined and wedges are simply obtained by solving equation (10) for each pair occupation-year. Hence, the model is able to perfectly fit the data (see Panel B of Figure C.5 in Appendix C), but its specification is in turn much less parsimonious than in our baseline. Column (3) in Table 5 shows the results for this specification. The inferred variance of discriminatory wedges, although it differs across years, is relatively stable from 2017 onwards, when immigration rates are higher and then occupational income gaps are more precisely estimated; and overall have on average a higher level (0.142) than in our baseline (0.100). Since time-variant wedges have now a larger explanatory power of the observed income gaps, the aggregate gains from both reforms are somewhat larger relative to

[29] For the remaining years, a comparison of the time series of the aggregate gains of each reform is displayed in Figure C.2 in Appendix C

[30] To make comparable the reduction in the variance of wedges between this specification and our baseline, we shrink the obtained variance in the same proportion than in our baseline Reform II, i.e. 47%.

our baseline results. Removing all frictions increases 1.28% in aggregate labor productivity (0.90% in our baseline), and leads to approximately half of the immigrants to reallocate in 2019 (30% in our baseline). Regarding Reform II, reducing the variance of wedges in the same proportion than in our baseline leads to a 0.53% aggregate gain and 13% of immigrants to reallocate, relative to 0.38% and 9% in our baseline, respectively. Therefore, the consequences for aggregate productivity are, although slightly larger, not very distant from our baseline results. This is due to the fact that the larger variances of the wedges are compensating the absence of type II frictions, while the cross-sectional variation in the inferred variances is playing an analogue role to the variation in time in α_{It}. In conclusion, we find this formulation of frictions delivers results that are not very different than our more parsimonious baseline specification.

6 Conclusions

Since immigrants frequently face additional obstacles in the labor market of the host-country before they are assimilated, their labor can be more misallocated than the labor of natives. In the case of sudden and massive migrations, this misallocation could lead to sizable macroeconomic implications for the host-country economy, particularly to its aggregate labor productivity. We document that this channel has a considerable impact in the case of the "Venezuelan exodus" to the Colombian economy in the period 2015-2019.

First, reduced-form evidence provides us signals about a greater amount of occupational misallocation for Venezuelan migrants relative to non-migrants. Particularly, the observed occupational allocation of immigrants given their educational attainment, and their significant residual income gaps even within-occupations, point in the direction of a larger amount of labor misallocation for immigrants. Second, when we examine those findings through the lens of a structural model of occupational choice, which takes into account workers who self-select across occupations due to unobservable skills, we are able to decompose how much of the observed residual income gaps are explained by sorting and how large the prevalent frictions must be for immigrants to generate the unexplained part. Armed with the model, we infer how costly those frictions are for the Colombian allocative efficiency. We find those frictions not only have a direct impact on the occupational allocation of immigrants, but also trigger general equilibrium effects that have consequences on the allocation of natives. By eliminating all frictions for immigrants, Colombian aggregate labor productivity could increase permanently by approximately 0.9%.

There are several avenues for future research. For tractability, our model abstracts from capital or the use of other inputs, so our implications for aggregate productivity are limited to the effect of labor misallocation only. But it is possible that this misallocation generates also inefficiencies in the use of other factors across occupations, magnifying the effects on the aggregate TFP. Further, in a model with capital, dynamic considerations could also start to matter. The study of dynamic inefficiencies induced by static factor misallocations, in a world where the losses in aggregate productivity are faced by generations that would not be necessarily the same as those who would benefit of immigrants assimilation (if the process spreads over a long period of time), is a fruitful road for future research. Finally, we made particular choices about the functional form of the talent distribution (Fréchet) and the specification of frictions, collecting previous ways in the literature to generate occupational misallocation of self-selecting workers while keeping the problem analytically tractable. There is room for further exploration of the consequences of moving towards more general specifications.

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Tables

Table 1 – Migrant Premia

	(1) Log income	(2) Log income	(3) Log income	(4) Log income	(5) Log income	(6) Log income
Migrant	-0.398***	-0.336***	-0.217***	-0.495***	-0.405***	-0.277***
	(0.068)	(0.057)	(0.043)	(0.030)	(0.034)	(0.031)
Gender	0.421***	0.530***	0.431***	0.208***	0.337***	0.215***
	(0.048)	(0.072)	(0.087)	(0.024)	(0.059)	(0.047)
Experience	0.057***	0.054***	0.049***	0.075***	0.066***	0.061***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Experience sq.	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education		0.111***	0.077***		0.112***	0.075***
		(0.003)	(0.003)		(0.002)	(0.002)
Observations	1,502,645	1,502,537	1,502,537	758,374	758,321	758,321
R-squared	0.186	0.346	0.401	0.145	0.359	0.406
Location FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Occupation FE	NO	NO	YES	NO	NO	YES

Notes: Columns (1)-(3) show the results of regression (1) for all workers, and columns (4) - (6) show the same results only for salaried workers. Observations weighted by survey expansion weights. Standard errors clustered by municipalities in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 2 – Migrant premia by occupation

Code	Short description for occupation	All workers		Only salaried workers	
		Premium	Std. error	Premium	Std. error
1	Administrative professionals and related	-0.431***	0.103	-0.331***	0.102
2	Security officers	-0.644***	0.029	-0.583***	0.021
3	Health professionals	-0.205*	0.105	-0.262**	0.106
4	Professors, chemists, biologists and related	-0.657***	0.103	-0.611***	0.093
5	Authors, composers and photographers	-0.178**	0.073	0.061	0.173
6	Managing directors	-0.197	0.211	-0.261	0.265
7	Unclassified administrative workers	-0.384***	0.046	-0.361***	0.035
8	Office accounting workers	-0.362***	0.109	-0.323***	0.057
9	Office assistants	-0.130	0.081	-0.176	0.114
10	Office transport workers	-0.272***	0.046	-0.341***	0.033
11	Merchants	-0.158***	0.029	-0.276***	0.050
12	Sales Workers	-0.484***	0.033	-0.541***	0.041
13	Salesmen	-0.325***	0.078	-0.322***	0.026
14	Hospitality workers	-0.179	0.106	-0.157***	0.040
15	Cooks, waiters and related	-0.114*	0.063	-0.153***	0.050
16	Personal service workers (helpers)	-0.124**	0.047	-0.135***	0.038
17	Cleaners, security guards and laundry	-0.433***	0.071	-0.356***	0.085
18	Hairdressers, beauticians and related	-0.025	0.037	-0.292***	0.034
19	Unclassified service workers	-0.535***	0.067	-0.605***	0.098
20	Agricultural workers	-0.033***	0.011	-0.174***	0.010
21	Metal and factory workers	-0.183*	0.093	-0.272**	0.099
22	Taylors, upholders and related workers	-0.179***	0.049	-0.418***	0.053
23	Shoemakers, carpenters and related workers	-0.119***	0.037	-0.226***	0.056
24	Mineral and stone processing operators	-0.372***	0.055	-0.368***	0.067
25	Machinery installers, watchmakers and related	-0.236***	0.055	-0.439***	0.021
26	Electricians, operators and handicraft workers	-0.262***	0.043	-0.384***	0.027
27	Building workers	-0.119***	0.032	-0.199***	0.027
28	Machine operators, packers and related	-0.455***	0.037	-0.443***	0.062
29	Vehicle drivers	-0.218***	0.048	-0.361***	0.053
30	Pawns in general, garbage collector and others	-0.293***	0.054	-0.427***	0.090

Notes: Columns "premium" and "std. errors" display the coefficient estimates and standard errors respectively of ϕ in the regression (1) for each occupation. Standard errors clustered by municipalities. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 3 – Results by year for baseline specification and parameterization

	$\forall\ t$	2015	2016	2017	2018	2019
A. Magnitudes of estimated frictions						
$Var\left[(1+\tau_{iI})\right]$	0.10			—		
$\alpha_{I,t}$		5.1%	3.8%	5.6%	8.1%	9.2%
α_N	4.7%			—		
B. Results of counterfactual exercises: Reform I						
- Productivity gains (%):						
Both types: $\tau_{iI} = \alpha_{I,t} = 0\ \forall\ i, t$		0.06	0.12	0.21	0.58	0.90
Only type I: $\tau_{iI} = 0\ \forall\ i$		0.05	0.09	0.16	0.40	0.61
Only type II: $\alpha_{I,t} = 0\ \forall\ t$		0.01	0.02	0.04	0.14	0.23
- Share of immigrants reallocated (%):						
Both types: $\tau_{iI} = \alpha_{I,t} = 0\ \forall\ i, t$		31.08	31.18	32.24	30.95	29.41
Only type I: $\tau_{iI} = 0\ \forall\ i$		30.00	30.40	30.93	29.31	27.92
Only type II: $\alpha_{I,t} = 0\ \forall\ t$		2.36	1.60	2.13	3.37	3.86
- Share of natives reallocated (%):						
Both types: $\tau_{iI} = \alpha_{I,t} = 0\ \forall\ i, t$		0.04	0.07	0.11	0.26	0.38
Only type I: $\tau_{iI} = 0\ \forall\ i$		0.03	0.07	0.11	0.25	0.36
Only type II: $\alpha_{I,t} = 0\ \forall\ t$		0.00	0.00	0.00	0.02	0.04
C. Results of counterfactual exercises: Reform II						
- Productivity gains (%):		0.02	0.04	0.08	0.24	0.38
- Share of workers reallocated (%):						
Immigrants:		10.21	10.31	10.55	9.69	9.11
Natives:		0.01	0.02	0.04	0.08	0.12

Notes: Reform I refers to the counterfactual of removing type I (discriminatory wedges, τ_{ig}) and type II (involuntary choices, α_{gt}) frictions for immigrants. Reform II refers to the counterfactual of equating both types of frictions for immigrants to the values of natives. Reform II assumes $\alpha_{It} = \alpha_N \forall\ t$ and a counterfactual variance of wedges equal to 0.047, a value derived from estimating the model only for natives with the subpopulations rural-men, urban-men, rural-women and urban-women, assuming only urban-men are not discriminated against. All results are computed using $\theta = 2.35$ and $\sigma = 3$.

Table 4 – Results for alternative parameterizations

	(1) Baseline	(2) Low θ	(3) High θ	(4) Low σ	(5) High σ
A. Calibrated parameters					
θ	2.35	1.50	3.50	2.35	2.35
σ	3.00	3.00	3.00	2.00	5.00
B. Magnitudes of estimated frictions					
$Var\left[(1+\tau_{iI})\right]$	0.100	0.118	0.105	0.100	0.100
$\alpha_{I,2015}$	5.1%	4.7%	5.1%	5.1%	5.1%
$\alpha_{I,2016}$	3.8%	3.6%	3.8%	3.8%	3.8%
$\alpha_{I,2017}$	5.6%	5.0%	5.8%	5.6%	5.6%
$\alpha_{I,2018}$	8.1%	6.7%	9.6%	8.1%	8.1%
$\alpha_{I,2019}$	9.2%	7.5%	11.0%	9.2%	9.2%
α_N	4.7%	5.5%	2.1%	4.7%	4.7%
C. Results of counterfactual exercises for 2019					
C.1. Reform I					
- Productivity gains (%):					
Both types: $\tau_{iI} = \alpha_{I,t} = 0 \ \forall \ i, t$	0.90	0.73	0.94	0.84	0.96
Only type I: $\tau_{iI} = 0 \ \forall \ i$	0.61	0.45	0.65	0.54	0.67
Only type II: $\alpha_{I,t} = 0 \ \forall \ t$	0.23	0.24	0.21	0.24	0.22
- Share of reallocated workers (%) $[immigrants, natives]$:					
Both types: $\tau_{iI} = \alpha_{I,t} = 0 \ \forall \ i, t$	$[29.4, 0.4]$	$[23.9, 0.1]$	$[39.4, 0.7]$	$[29.3, 0.5]$	$[29.6, 0.3]$
Only type I: $\tau_{iI} = 0 \ \forall \ i$	$[27.9, 0.4]$	$[22.9, 0.1]$	$[36.3, 0.7]$	$[27.8, 0.5]$	$[28.0, 0.2]$
Only type II: $\alpha_{I,t} = 0 \ \forall \ t$	$[3.9, 0.0]$	$[3.1, 0.0]$	$[4.7, 0.1]$	$[3.9, 0.0]$	$[3.9, 0.0]$
C.2. Reform II					
- Productivity gains (%):	0.38	0.30	0.46	0.36	0.39
- Share of reallocated workers (%) $[immigrants, natives]$:	$[9.1, 0.1]$	$[9.1, 0.1]$	$[12.3, 0.2]$	$[9.1, 0.2]$	$[9.2, 0.1]$

Notes: Reform I refers to the counterfactual of removing type I (discriminatory wedges, τ_{ig}) and type II (involuntary choices, α_{gt}) frictions for immigrants. Reform II refers to the counterfactual of equating both types of frictions for immigrants to the values of natives. Reform II assumes $\alpha_{It} = \alpha_N \forall \ t$ and a counterfactual variance of wedges equal to 0.047, a value derived from estimating the model only for natives with the subpopulations rural-men, urban-men, rural-women and urban-women, assuming only urban-men are not discriminated against.

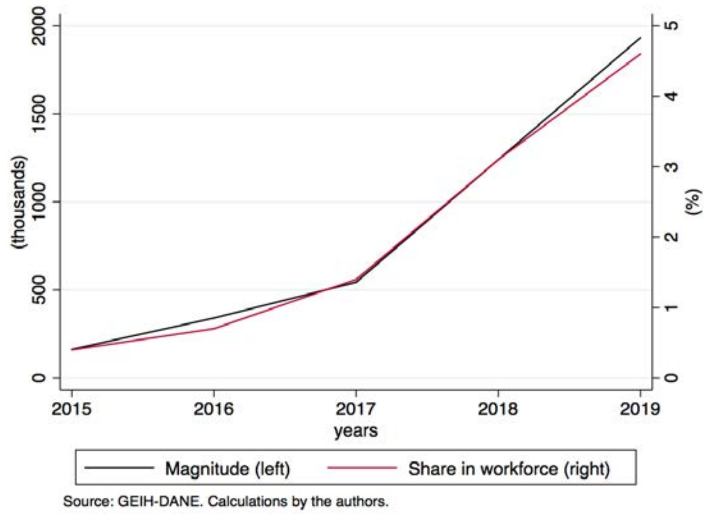
Table 5 – Results for baseline and alternative specifications

	(1) Baseline	(2) Inferring $\frac{\bar{h}_{iI}}{\bar{h}_{iN}}$	(3) Time-variant $(1+\tau_{itI})$
A. Magnitudes of estimated frictions			
$Var\left[(1+\tau_{iI})\right]$	0.100	0.162	0.142
$Var\left[\frac{\bar{h}_{iI}}{\bar{h}_{iN}}\right]$	–	0.164	–
$Var\left[(1+\tau_{iI,2015})\right]$	–	–	0.106
$Var\left[(1+\tau_{iI,2016})\right]$	–	–	0.170
$Var\left[(1+\tau_{iI,2017})\right]$	–	–	0.149
$Var\left[(1+\tau_{iI,2018})\right]$	–	–	0.142
$Var\left[(1+\tau_{iI,2019})\right]$	–	–	0.145
$\alpha_{I,2015}$	5.1%	4.5%	–
$\alpha_{I,2016}$	3.8%	2.9%	–
$\alpha_{I,2017}$	5.6%	5.2%	–
$\alpha_{I,2018}$	8.1%	7.7%	–
$\alpha_{I,2019}$	9.2%	9.0%	–
α_N	4.7%	0.7%	–
B. Results of counterfactual exercises for 2019			
B.1. Reform I			
- Productivity gains (%):			
Both types: $\tau_{iI} = \alpha_{I,t} = 0 \; \forall \; i, t$	0.90	0.52	1.28
Only type I: $\tau_{iI} = 0 \; \forall \; i$	0.61	0.29	1.28
Only type II: $\alpha_{I,t} = 0 \; \forall \; t$	0.23	0.21	–
- Share of reallocated workers (%) $[immigrants, natives]$:			
Both types: $\tau_{iI} = \alpha_{I,t} = 0 \; \forall \; i, t$	$[29.4, 0.4]$	$[21.4, 0.3]$	$[51.9, 0.6]$
Only type I: $\tau_{iI} = 0 \; \forall \; i$	$[27.9, 0.4]$	$[19.0, 0.2]$	$[51.9, 0.6]$
Only type II: $\alpha_{I,t} = 0 \; \forall \; t$	$[3.9, 0.0]$	$[3.8, 0.0]$	–
B.2. Reform II			
- Productivity gains:	0.38	0.31	0.53
- Share of reallocated workers (%) $[immigrants, natives]$:	$[9.1, 0.1]$	$[7.6, 0.1]$	$[12.9, 0.2]$

Notes: Reform I refers to the counterfactual of removing type I (discriminatory wedges, τ_{ig}) and type II (involuntary choices, α_{gt}) frictions for immigrants. Reform II refers to the counterfactual of equating both types of frictions for immigrants to the values of natives. Reform II assumes $\alpha_{It} = \alpha_N \forall \; t$ and a counterfactual variance of wedges equal to 47% the estimated variance, a value derived from the ratio between the observed and the counterfactual variance in the baseline specification.

Figures

Figure 1 – Migrants Inflow and Share in Colombian Workforce

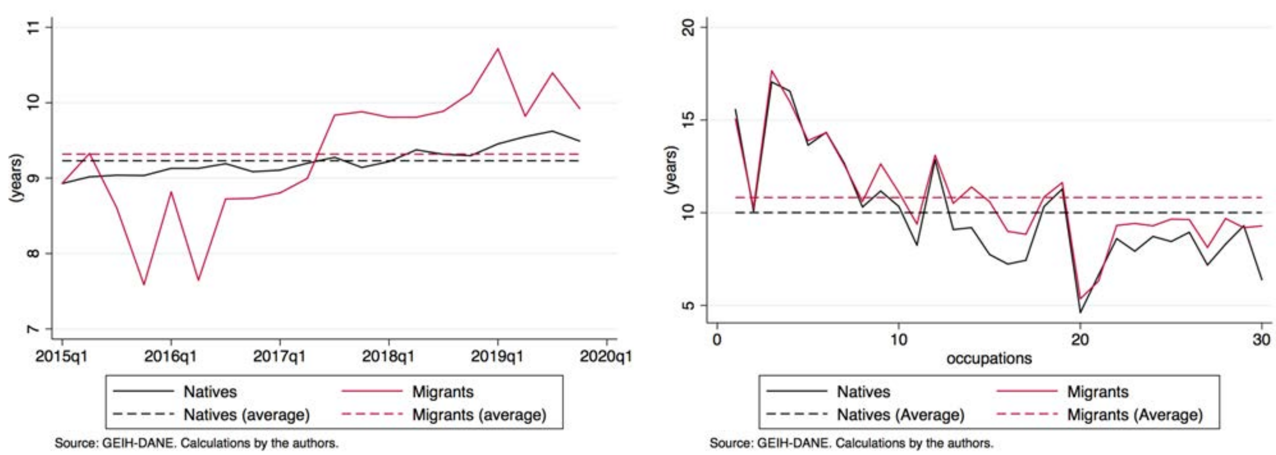


Notes: Figure shows the evolution of the inflow of immigrants from Venezuela to Colombia over 2015-2019 and how much they represent in terms of the Colombian workforce. Observations are weighted by survey expansion weights.

Figure 2 – Average Years of Education: Migrants vs. Natives

(a) Over Time

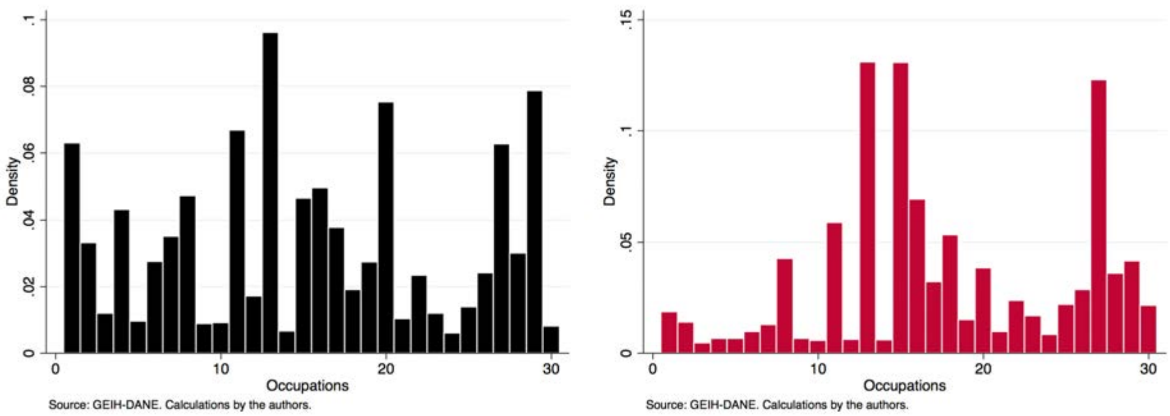
(b) By Occupations



Notes: Panel A shows the average years of education of natives and immigrants aged 25 years and older in each quarter of the period 2015-2019 and the corresponding averages over all quarters. Panel B shows the average years of education of natives and immigrants in each occupation (for the pooled data) and the corresponding averages over all occupations. Observations are weighted by survey expansion weights.

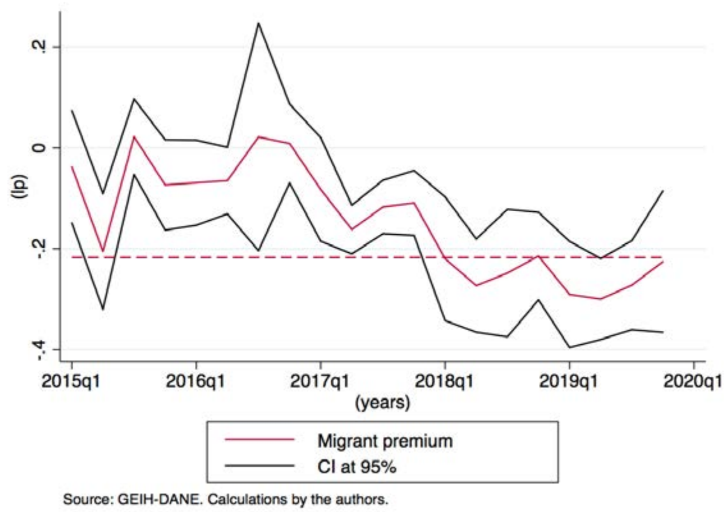
Figure 3 – Occupational Distribution

(a) Natives **(b)** Migrants



Notes: Figure shows the occupational distribution of Natives (Panel A) and Immigrants (Panel B) in the pooled data. Observations are weighted by survey expansion weights.

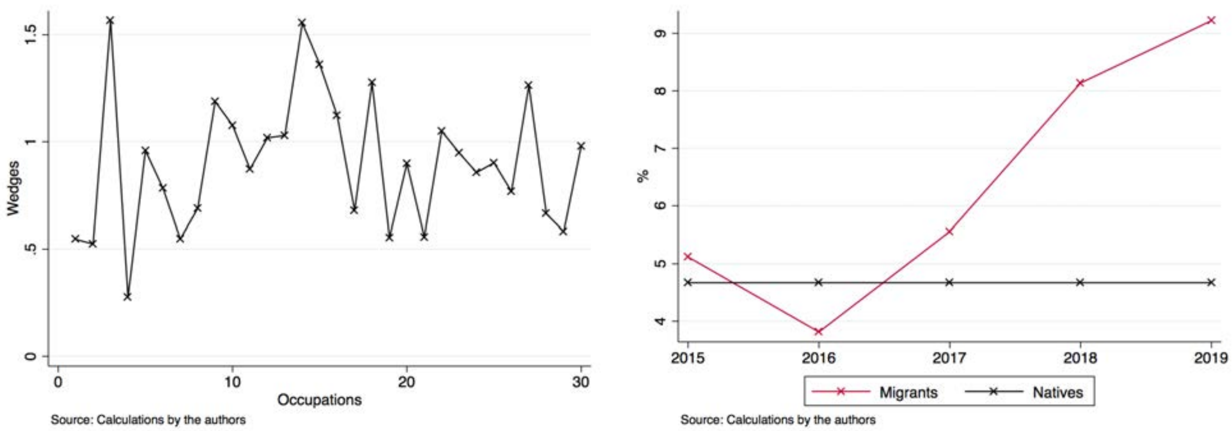
Figure 4 – Migrant Premium over Time



Notes: Figure shows the evolution of the migrant premium, computed using regression (1) for all workers controlling for occupational fixed-effects, for each quarter of the period 2015-2019, and its corresponding 95% confidence interval. The dashed line corresponds to the migrant premium in the pooled data controlling also for time fixed-effects (column (3) of Table 1). Standard errors are clustered by municipalities, and observations are weighted by survey expansion weights.

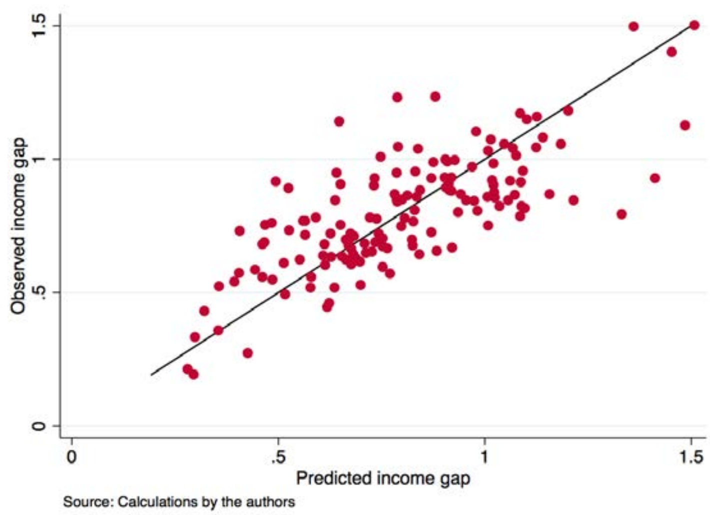
Figure 5 – Estimated Frictions under the Baseline Parametrization

(a) Discriminatory wedges $(1 + \tau_{iI})$ **(b)** Fractions of involuntary choices α_{gt}



Notes: Figure shows in Panel A the inferred values of the discriminatory wedges for immigrants in each occupation, $(1 + \tau_{iI})$, which have a variance equal to 0.100, and in Panel B the inferred values of the fractions of involuntary choices for immigrants (α_{It}) and for natives (α_N). Both frictions are inferred using $\theta = 2.35$.

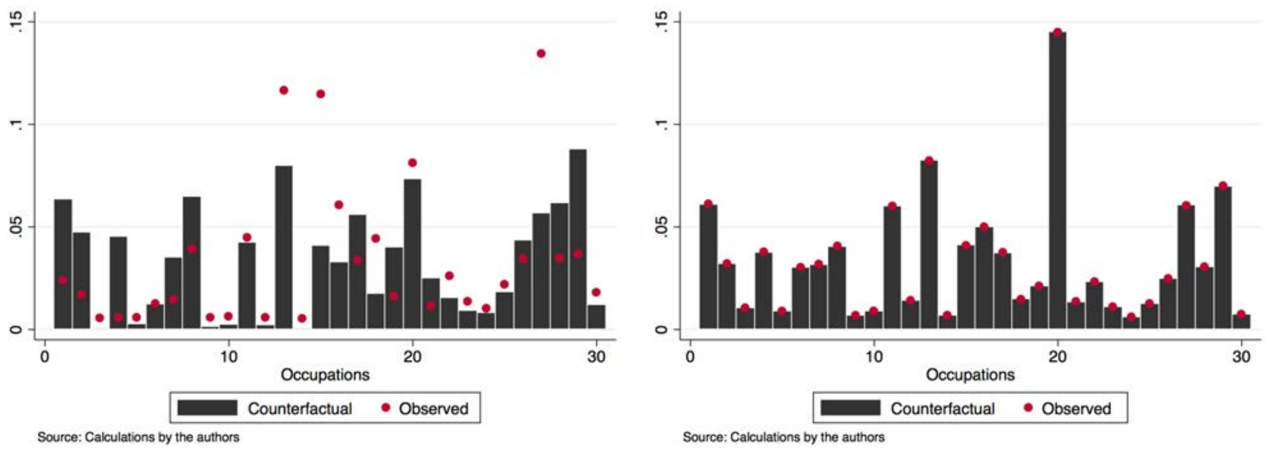
Figure 6 – Model Fit under Estimated Frictions



Notes: Figure shows the observed income gaps with predicted income gaps under our set of estimated frictions $\{(1 - \tau_{iI}), \alpha_{It}, \alpha_N\}$ using the RHS of equation 10 , and a $45°$ line.

Figure 7 – Counterfactual occupational distributions (Reform I)

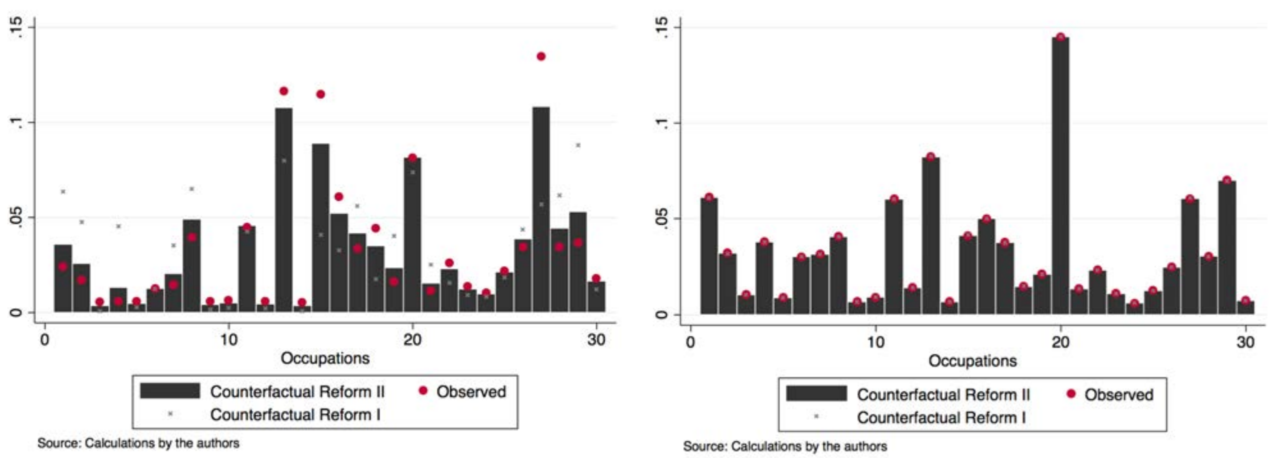
(a) Migrants **(b)** Natives



Notes: Figure shows the occupational distribution of Immigrants (Panel A) and Natives (Panel B) in the pooled data after Reform I is implemented, compared to the actual distributions.

Figure 8 – Counterfactual Occupational Distributions (Reform II)

(a) Migrants **(b)** Natives



Notes: Figure shows the occupational distribution of Immigrants (Panel A) and Natives (Panel B) in the pooled data after Teform II is implemented, compared to the actual distributions and the derived from Reform I.

Appendix

A Data

A.1 Database

Our dataset comes from the Colombian Wide-scale Integrated Household Survey (GEIH by its acronym in Spanish) produced by the National Administrative Department of Statistics (DANE by its acronym in Spanish), the official statistics bureau in Colombia. The GEIH is the largest monthly statistical operation in the country, with around 21 thousand face-to-face surveys per month in the 23 main metropolitan areas and a rural aggregate. For each household interviewed, the survey provides individual information regarding working conditions (employment status, economic activity, occupation, earnings, expenditures and affiliation to social security) and socio-demographic characteristics such as gender, age, marital status, education, living conditions among other relevant variables.

Since mid-2013 the survey included an additional questionnaire about migration, in which respondents are asked whether they lived in the country five years ago and twelve months ago. Respondents with negative answers in any of those two questions are also asked about the country of precedence. These two questions allow us to identify immigrants and recent immigrants from Venezuela; the former category is what we employ to define an immigrant. For our analysis, we consider only individuals in working age, and exclude those who report being unemployed or outside the labor force (students, retirees, etc.). Table A.1 provides for each year the original sample sizes from GEIH and the resulting ones used in our analysis excluding both unemployed and inactive people. The table also shows the share of the sample in each year that pertains to immigrants and non-migrants for both panels, and some demographic characteristics of both populations such as share of males, average age and average years of schooling.

A.2 Occupations

We reclassified DANE's original set of 99 occupations into 30 new categories, applying the following three rules. First, no reclassification was made for an occupation with a high frequency of workers. Second, occupations with low concentration of workers were added to the most similar job (e.g. firemen, policemen and soldiers were included in security officers) taking as baseline the International Standard Classification of Occupations. Third, few low-frequency occupations with no similar jobs were dropped (e.g. clergy members, athletes). Table A.2 lists the 30 occupational groupings we use. Table A.2 also reports the average years of education in each occupation for both immigrants and non-migrants. Notice that the average years of education tend to be decreasing with the occupational code.

A.3 Labor Income

GEIH includes at least 15 questions related to labor and non-labor earnings. We construct six different labor income measures aggregating the answers to different questions related to labor earnings. Table A.3 lists the 6 different income measures we use, and describes the differences among them. For the main results in this paper we use the measure "Incomesuma". Our results are robust to the choice of any of these income measures.

Table A.1 – Sample statistics by year

	2015	2016	2017	2018	2019
Panel A: Database using only employees					
Sample size	308.632	302.263	294.083	292.922	308.404
Non-Migrants					
% Non-Migrants	99.5	99.2	98.5	96.8	95.3
% Male	54.9	54.8	55.0	55.2	55.4
Average Age	39.5	39.7	40.1	40.5	41.0
Average Years of Schooling	9.2	9.3	9.3	9.5	9.7
Migrants					
% Migrants	0.4	0.7	1.4	3.1	4.6
% Male	61.2	62.9	59.4	60.2	59.3
Average Age	36.0	35.3	34.5	33.5	33.3
Average Years of Schooling	8.4	8.5	9.4	9.9	10
Panel B: Original Database					
Sample size	787.044	778.238	767.867	762.753	756.063
Non-Migrants					
% Share in the total	99.6	99.2	98.7	97.4	96.0
% Male	47.0	47.1	47.1	47.1	47.0
Average Age	31.2	31.4	31.7	32.0	32.3
Average Years of Schooling	6.8	6.9	7.0	7.1	7.2
Migrants					
% Share in the total	0.4	0.7	1.3	2.6	3.9
% Male	49.8	50.4	49.4	49.5	48.1
Average Age	29.0	28.3	27.7	27.6	27.3
Average Years of Schooling	6.9	6.8	7.4	8.0	8.0

Notes: Panel A refers to the original database excluding unemployed and people outside the labor force. Source: GEIH - DANE.

Table A.2 – Occupation categories

Code	Occupation description	Average years of education	
		Non-migrants	Migrants
1	Administrative professionals and those related to architecture	10.1	10.2
2	Security officers (captains, pilots, inspectors, etc.)	16.9	17.6
3	Health professionals	16.3	15.3
4	Teaching professionals and scientists (chemists, biologists, etc.)	13.4	13.2
5	Authors, composers and photographers	13.9	13
6	Managing directors	12.5	12.4
7	Unclassified administrative workers	10.6	10.7
8	Office accounting workers	11.4	12.4
9	Office assistants	10.3	11.2
10	Office transport workers	8.4	9.4
11	Merchants, owners of wholesale and retail trade	12.8	12.5
12	Head of sales, insurance & real estate agents, brokers and related	9.4	10.4
13	Salesmen	9.3	11.4
14	Hospitality workers	8.3	10.7
15	Cooks, waiters and related	7.4	9.1
16	Personal service workers (helpers)	7.6	8.9
17	Cleaners, security guards and laundry workers	10.3	10.7
18	Hairdressers, beauticians and related workers	11.3	11.4
19	Unclassified service workers	5.0	5.9
20	Agricultural workers	6.8	6.3
21	Metal and factory workers	8.7	9.3
22	Tailors, upholsterers and related workers	8.1	9.5
23	Shoemakers, carpenters and related workers	8.8	9.3
24	Mineral and stone processing operators	8.6	9.5
25	Machinery installers, watchmakers and related workers	9.1	9.7
26	Electricians, operators and handicraft workers	7.4	8.2
27	Construction workers	8.5	9.7
28	Machine operators, packers and related workers	9.4	9.2
29	Vehicle drivers	6.8	9.2
30	Pawns, garbage collectors, polishers and related	6.8	9.2

Table A.3 – Labor income measures

No.	Name	Definition
1	Income	Answer to the question "How much did you earned the last month?"
2	Incomesum	"Income" plus reported extra earnings such as bonuses, subsidies, etc.
3	Incomewoa	"Income" minus extra earnings for those who included them in "Income"
4	Incomesuma	"Incomesum" minus extra earnings for those with missing "Income"
5	Incomeadj10	"Income" plus earnings related to labor/business activities for non-salaried individuals, trimmed in 10k Colombian pesos (3 USD).
6	Incomeadj1	"Income" plus earnings related to labor/business activities for non-salaried individuals, trimmed in 1k Colombian pesos (0.3 USD).

B Derivations, Proofs and Additional Procedures

B.1 Equilibrium Definitions

The competitive equilibrium of the model for each period t consists on a set of individual occupational choices, total efficiency units of labor of each group in each occupation H_{igt}, total output Y_t and an efficiency wage w_{it} in each occupation such that: i) each individual chooses the occupation that maximizes V_{igt} according to equation (5), ii) the representative firm hires H_{igt} in each occupation to maximize profits; iii) total output Y_t is given by the production function in equation (6); and iv) w_{it} clears each occupational labor market. Therefore, the solution for efficiency wages w_{it} in general equilibrium can be obtained from the following conditions:

1. The definition of the total supply of efficiency units of labor of each group in each occupation, H_{igt}^{supply}, which aggregates individual choices:

$$H_{igt}^{supply} = q_{gt} p_{igt} \mathbb{E}\left(h_{igt} \epsilon_{ig}\right) \tag{B.1}$$

2. The definition of the total demand of efficiency units of labor of each group in each occupation, H_{igt}^{demand}, given by firm profit maximization:

$$H_{igt}^{demand} = A_{it}^{\sigma-1} w_{it}^{-\sigma} Y_t \tag{B.2}$$

3. Total output given by the production function in equation (6), which in equilibrium is also equal to aggregate wages plus total revenues from τ:

$$Y_t = \sum_i \sum_g w_{it} \mathbb{E}\left(h_{igt} \epsilon_{ig}\right) \tag{B.3}$$

4. w_{it} is the value that clears each occupational labor market:

$$H_{igt}^{supply} = H_{igt}^{demand} \tag{B.4}$$

B.2 Proof of Proposition 1

Proof. First, consider the occupational choices when every worker can pick their occupation voluntarily, i.e. with only type I frictions. In this case, the proof essentially mirrors that of Hsieh et al. (2019), so we outline the main steps. The worker's problem at each time t is to choose the occupation with the largest value of $\widetilde{w}_{igt}\epsilon_i$. Hence, $\widetilde{p}_{igt}$ is given by:

$$\begin{aligned}
\widetilde{p}_{igt} &= \Pr\left[\widetilde{w}_{igt}\epsilon_i > \widetilde{w}_{sgt}\epsilon_s\right] \forall s \neq i \\
&= \Pr\left[\epsilon_s < \widetilde{w}_{igt}\epsilon_g / \widetilde{w}_{sgt}\right] \forall s \neq i \\
&= \int F_i \left(\frac{\widetilde{w}_{igt}}{\widetilde{w}_{1gt}} \epsilon_1, \frac{\widetilde{w}_{igt}}{\widetilde{w}_{2gt}} \epsilon_2, \ldots, \epsilon_i, \ldots, \frac{\widetilde{w}_{igt}}{\widetilde{w}_{Ogt}} \epsilon_O \right) d\epsilon
\end{aligned} \tag{B.5}$$

where $F_i(\cdot)$ is the derivative of the cdf funcion given in (3) with respect to its i-th argument. Given the arguments in (B.5) such derivative is:

$$F_i \left(\frac{\widetilde{w}_{igt}}{\widetilde{w}_{1gt}} \epsilon_1, \frac{\widetilde{w}_{igt}}{\widetilde{w}_{2gt}} \epsilon_2, \ldots, \epsilon_i, \ldots, \frac{\widetilde{w}_{igt}}{\widetilde{w}_{Ogt}} \epsilon_O \right) = \theta \epsilon_i^{-\theta-1} \cdot \exp\left[\sum_s \left(\frac{\widetilde{w}_{igt}}{\widetilde{w}_{sgt}} \right)^{-\theta} \epsilon^{-\theta} \right]$$

Notice that $\frac{dF(\epsilon)}{d\epsilon} = \sum_s \left(\frac{\widetilde{w}_{igt}}{\widetilde{w}_{sgt}}\right)^{-\theta} \theta\epsilon_s^{-\theta-1} \exp\left[\sum_s \left(\frac{\widetilde{w}_{igt}}{\widetilde{w}_{sgt}}\right)^{-\theta} \epsilon^{-\theta}\right]$ so evaluating the integral in (B.5) gives:

$$\widetilde{p}_{igt} = \frac{1}{\sum_s \left(\frac{\widetilde{w}_{igt}}{\widetilde{w}_{sgt}}\right)^{-\theta}} \cdot \int dF(\epsilon) = \frac{\widetilde{w}_{igt}^{\theta}}{\sum_s \widetilde{w}_{sgt}^{\theta}} \tag{B.6}$$

Introducing type II frictions implies that a fraction α_{gt} of workers cannot choose their preferred occupation and simply end up randomly allocated in any other occupation. So the share of workers from group g who ends in occupation i at time t, p_{igt} is given by:

$$p_{igt} = (1-\alpha_{gt})\,\widetilde{p}_{igt} + \alpha_{gt}\left(\frac{1}{M}\right) \tag{B.7}$$

equations (B.6) and (B.7) constitute equation (8) in the text, the first part of Proposition 1.

Now, for the second part, the geometric average of abilities of the group g in an occupation j is given by:

$$\begin{aligned}\exp^{\mathbb{E}[\log(\epsilon_i)]} &= \exp^{\{(1-\delta_{igt})\mathbb{E}[\log(\epsilon_i|\text{choose } i)]+\delta_{igt}\mathbb{E}(\log\epsilon_i)\}} \\ &= \left[\exp^{\mathbb{E}[\log(\epsilon_i|\text{choose } i)]}\right]^{1-\delta_{igt}} \left[\exp^{\mathbb{E}(\log\epsilon_i)}\right]^{\delta_{igt}}\end{aligned} \tag{B.8}$$

with δ_{igt} defined as in the text. Since ϵ_i is distributed Fréchet with parameter θ, $\log\epsilon_i$ is distributed Gumbel with parameter $1/\theta$. Thus, $\mathbb{E}(\log\epsilon_i)$, the unconditional mean of a Gumbel is equal to $\frac{\gamma_{em}}{\theta}$, where $\gamma_{em}\approx 0.5772$ is the Euler–Mascheroni constant; and hence $\exp^{\mathbb{E}(\log\epsilon_i)}$, equal to the unconditional geometric mean of the Fréchet distribution, is given by $\widetilde{\Gamma} \equiv e^{\frac{\gamma_{em}}{\theta}}$. To obtain an expression for $e^{\mathbb{E}\log[\epsilon_i|\text{choose } i]}$, the geometric mean of abilities for individuals who can work in their occupation choice, we proceed as in Hsieh et al. (2019). Denote with stars the variables in the chosen occupation, e.g. ϵ^* denotes the ability in the chosen occupation. Properties of the Fréchet distribution imply that the distribution $G(\epsilon)$ of ϵ^*, the extreme value of ϵ, is also the following Fréchet:

$$G(\epsilon) \equiv \Pr[\epsilon^* < \epsilon] \equiv \exp\left[\sum_s \left(\frac{\widetilde{w}_{gt}^*}{\widetilde{w}_{sgt}}\right)^{-\theta} \epsilon^{-\theta}\right],$$

Denoting $\widetilde{p}_{gt}^* = \frac{\widetilde{w}_{gt}^*}{\sum_s \widetilde{w}_{sgt}^{\theta}}$ according with the definition of $\widetilde{p}_{igt}$ in (B.6), we obtain:

$$\begin{aligned}\mathbb{E}[\epsilon^*] &= \int_0^\infty \epsilon^* dG(\epsilon^*) \\ &= \int_0^\infty \theta\left(\frac{1}{\widetilde{p}_{gt}^*}\right)\epsilon^{*(-\theta-1)} e^{-\left(\frac{1}{\widetilde{p}_{gt}^*}\right)\epsilon^{*-\theta}} d\epsilon^*.\end{aligned}$$

The Gamma function is $\Gamma(\alpha) \equiv \int_0^\infty x^{\alpha-1}e^{-x}dx$. Using the change of variable $x \equiv \frac{1}{p^*}\epsilon^{*-\theta}$, it is possible to show that:

$$\mathbb{E}[\epsilon^*] = \left(\frac{1}{\widetilde{p}_{gt}^*}\right)^{1/\theta} \int_0^\infty x^{-\frac{1}{\theta}} e^{-x} dx = \bar{\Gamma}\left(\frac{1}{\widetilde{p}_{gt}^*}\right)^{1/\theta} \tag{B.9}$$

where $\bar{\Gamma} \equiv \Gamma\left(1-\frac{1}{\theta}\right)$ is the unconditional mean of the Fréchet distribution with parameter θ. Substituting this result for occupation i in (B.8) and using the unconditional geometric mean of the Fréchet distribution, we obtain:

$$\exp^{\mathbb{E}[\log(\epsilon_i)]} = \left[\widetilde{\Gamma}\left(\frac{1}{\widetilde{p}_{igt}}\right)^{1/\theta}\right]^{1-\delta_{igt}} \left[\widetilde{\Gamma}\right]^{\delta_{igt}}$$
$$= \widetilde{\Gamma}\left(\frac{1}{\widetilde{p}_{igt}}\right)^{\frac{1}{\theta}(1-\delta_{igt})} \tag{B.10}$$

(B.10) is equal to equation (9) in the text, the second part of Proposition 1. □

B.3 Procedure to Derive z_{igt}, A_{it}, w_{it} and Y_t in the Observed Economy

In the initial equilibrium, the values of $\widehat{y}_{igt}$, $\widehat{x}_{igt}$, p_{igt} and q_{gt} are observables, τ_{ig} and α_{gt} are our estimated frictions, and σ and θ are calibrated parameters. With this set of information, the following steps describe how to derive the values of z_{igt}, A_{it}, w_{it} and Y_t.

1. With values of p_{igt} and α_{gt}, use equation (8) and the definition of δ_{igt} to derive $\widetilde{p}_{igt}$ and δ_{igt}.
2. With values of $\widehat{y}_{iNt}$, $\widehat{x}_{iNt}$, $\widetilde{p}_{iNt}$, δ_{iNt} and θ, use $\widehat{y}_{iNt} = w_{it}\overline{h}_{iN}\widehat{x}_{iNt}\left(\widetilde{p}_{iNt}\right)^{\frac{1}{\theta}(\delta_{iNt}-1)}$, the geometric average of the income of natives, to derive $w_{it}\overline{h}_{iN}$.
3. Using the identifying assumption $\overline{h}_{ig} = 1$ made for the baseline results (or in the case of the robustness exercises where $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ is estimated, the normalization $\overline{h}_{iN} = 1$), w_{it} is equal to $w_{it}\overline{h}_{iN}$.
4. For natives, with values $\widehat{x}_{1Nt}$, w_{1t} and θ, use the normalization $z_{1Nt} = 1$ to derive $\widetilde{w}^{\theta}_{1Nt}$ from the definition of $\widetilde{w}_{igt}$ in the text. For immigrants, use the normalization $z_{1It} = 1$, the assumption $\overline{h}_{1I} = 1$ (or the estimated value of $\frac{\overline{h}_{1I}}{\overline{h}_{1N}}$ in the robustness exercises) to derive $\widetilde{w}^{\theta}_{1It}$ with the values $\widehat{x}_{1It}$, τ_{1I}, $w_{1t}\overline{h}_{1I}$ and θ.
5. Denote $m_{gt} = \sum_s \widetilde{w}^{\theta}_{sgt}$, so $\widetilde{p}_{igt} = \frac{\widetilde{w}^{\theta}_{igt}}{m_{gt}}$. With the values of $\widetilde{p}_{1gt}$ and $\widetilde{w}^{\theta}_{1gt}$, derive m_{gt}.
6. For $i \neq 1$, with the values of m_{gt}, $\widetilde{p}_{iNt}$, τ_{ig}, w_{it}, $\overline{h}_{ig}$, $\widehat{x}_{iNt}$ use the definition of $\widetilde{w}_{igt}$ and $\widetilde{p}_{igt} = \frac{\widetilde{w}^{\theta}_{igt}}{m_{gt}}$ to derive z_{igt}.
7. Properties of the Fréchet distribution imply that if the geometric average of ϵ_{it} is given by equation (9), its arithmetic average is then $\bar{\Gamma}\left[(1-\delta_{igt})\left(\frac{1}{\widetilde{p}_{igt}}\right)^{\frac{1}{\theta}} + \delta_{igt}\right]$, with $\bar{\Gamma}$ defined as in equation (B.9). Thus, compute the supply of efficiency units of labor for each occupation-group H^{supply}_{igt} from equation (B.1) using the definition of the arithmetic average and the values of δ_{igt}, θ, $\widetilde{p}_{igt}$, p_{igt} and q_{gt} and the assumption $\overline{h}_{ig} = 1$ (or the estimated values of $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ in the robustness exercises).
8. The aggregate supply of efficiency units of labor for each occupation, H^{supply}_{it}, is simply the sum of the supply for each occupation-group, $H^{supply}_{it} = H^{supply}_{iIt} + H^{supply}_{iNt}$
9. In general equilibrium, total output is equal to aggregate wages (discounting discriminatory taxes for immigrants) plus total revenues from τ, and hence: $Y_t = \sum_i w_{it}H^{supply}_{it}$
10. Finally, using the fact that each occupational labor market must be clear, so $H^{demand}_{igt} = H^{supply}_{igt}$, from the expression of the total demand of efficiency units of labor given in (B.3), derive A_{it} with values of H^{supply}_{igt}, Y_t, w_{it} and σ.

B.4 Procedure to Derive p_{igt}, w_{it} and Y_t for the Counterfactual Economy

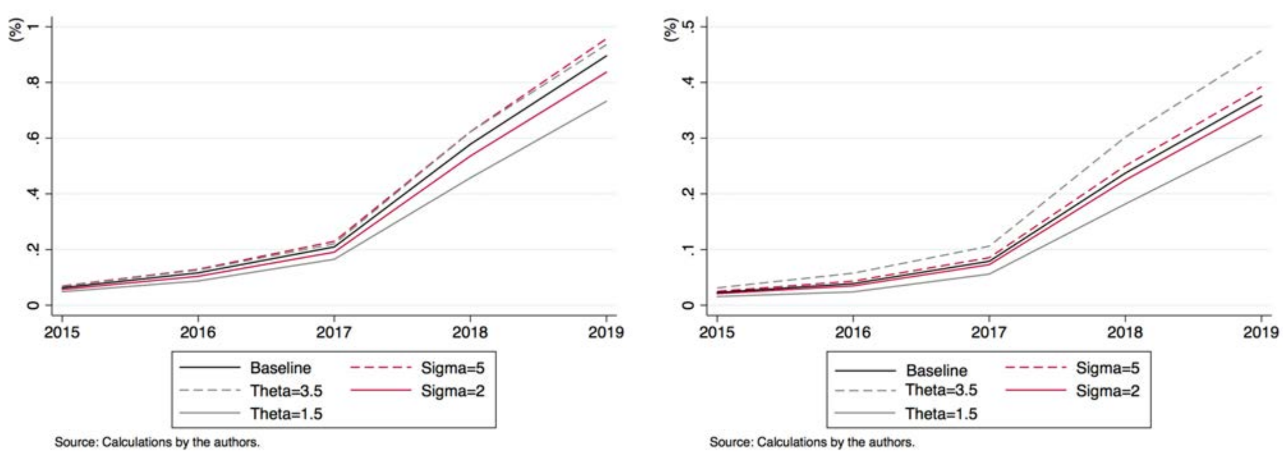
In the counterfactual equilibrium, the values of q_{gt}, $\widehat{x}_{igt}$, $\overline{h}_{ig}$, z_{igt}, A_{it}, σ and θ are the same as in the observed economy and τ^c_{ig} and α^c_{gt} are our intended frictions (hereafter superscript c denotes counterfactual values). With this set of information, the following fixed-point algorithm describes how to derive the values of p^c_{igt}, w^c_{it} and Y^c_t for the counterfactual economy.

1. Guess a value of w^c_{it}. Start with $w^c_{it} = w_{it}$.
2. With values of w^c_{it}, τ^c_{ig} $\widehat{x}_{igt}$, $\overline{h}_{ig}$, z_{igt} and θ, derive $\widetilde{p}^c_{igt}$ from its definition.
3. With values of α^c_{gt} and $\widetilde{p}^c_{igt}$ use equation (8) and the definition of δ_{igt} to derive p^c_{igt} and δ^c_{igt}.
4. Use the definition of the arithmetic average of ϵ_{it} in step 7 of Appendix (B.3), and the definition of the supply of efficiency units of labor for each occupation-group from equation (B.1), to compute $H^{supply,c}_{igt}$ with the values of δ^c_{igt}, θ, $\widetilde{p}^c_{igt}$, p^c_{igt} and q_{gt}.
5. The aggregate supply of efficiency units of labor for each occupation, $H^{supply,c}_{it}$, is the sum of the supply for each occupation-group, $H^{supply,c}_{it} = H^{supply,c}_{iIt} + H^{supply,c}_{iNt}$
6. With values of p^c_{igt}, A_{it}, σ, $H^{supply,c}_{igt}$, q_{gt} use the CES production function in equation (6) to derive Y^c_t.
7. From the expression of the total demand of efficiency units of labor given in (B.3), and using the fact $H^{demand}_{igt} = H^{supply}_{igt}$, compute the efficiency wages $w^{c'}_{it}$ compatible with Y^c_t, A_{it}, σ, $H^{supply,c}_{it}$.
8. Substitute w^c_{it} by $w^{c'}_{it}$ in step 1 an repeat steps 2-7 until $w^{c'}_{it} \approx w^c_{it}$.

C Additional Figures

Figure C.1 – Gains from Reforms by Year: Robustness to Parameterization

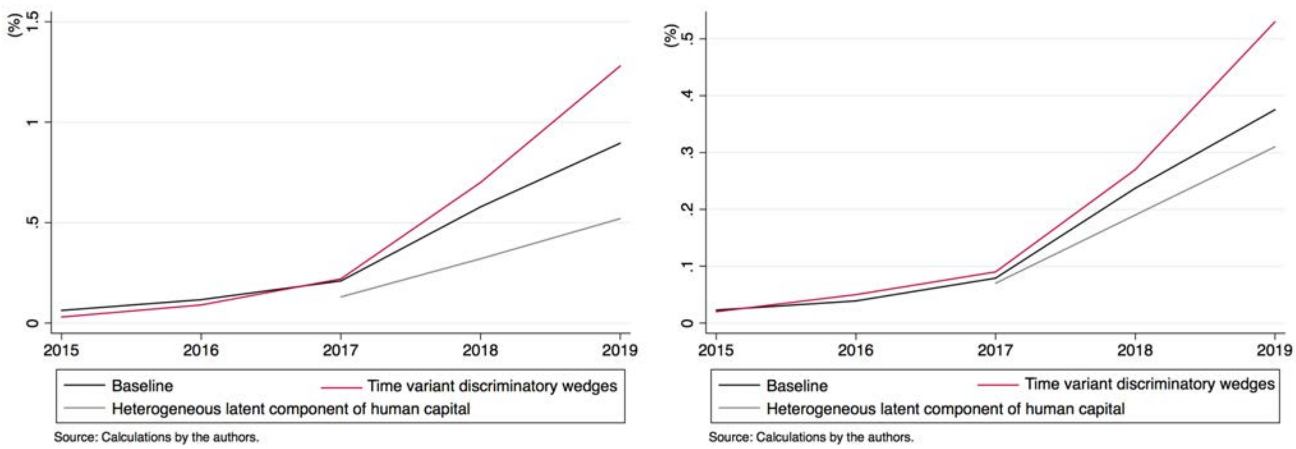
(a) Reform I **(b)** Reform II



Notes: Figure shows in Panel A the gains from the complete Reform I ($\tau_{iI} = \alpha_{I,t} = 0 \;\forall\; i, t$) for each year of the "Venezuelan exodus" depending on the values θ and σused (baseline parameterization uses $\theta = 2.35$ and $\sigma = 3$) and in Panel B the same comparison for Reform II.

Figure C.2 – Gains from Reforms by Year: Robustness to Specification

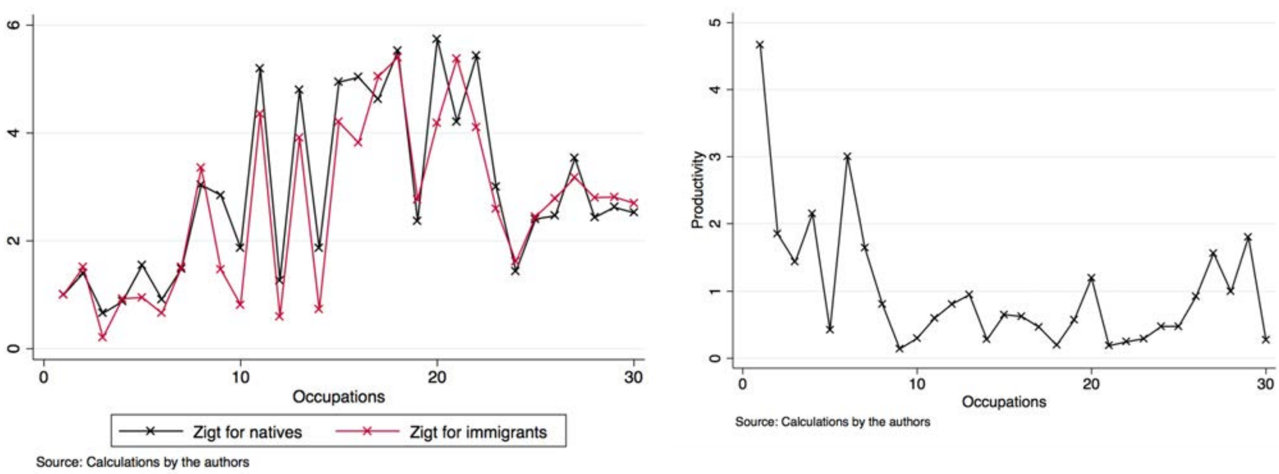
(a) Reform I **(b)** Reform II



Notes: Figure shows in Panel A the gains from the complete Reform I ($\tau_{iI} = \alpha_{I,t} = 0 \; \forall \; i, t$) for each year of the "Venezuelan exodus" depending on the model specification chosen, and in Panel B the same comparison for Reform II.

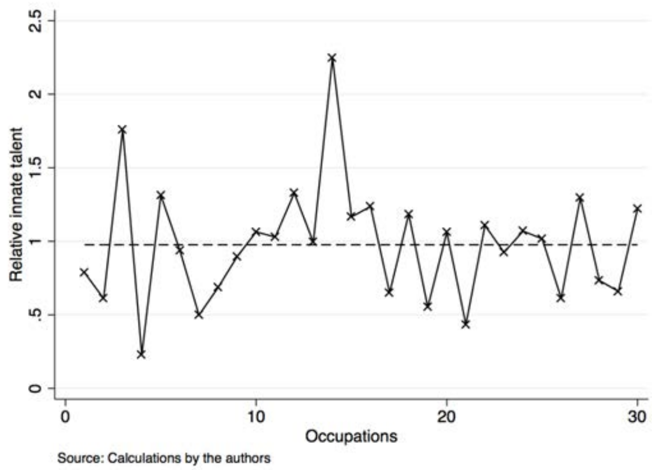
Figure C.3 – Average Group-specific Preferences and Productivities in the Baseline

(a) Group-specific Preferences $\bar{z}_{ig}$ **(b)** Productivities $\bar{A}_t$



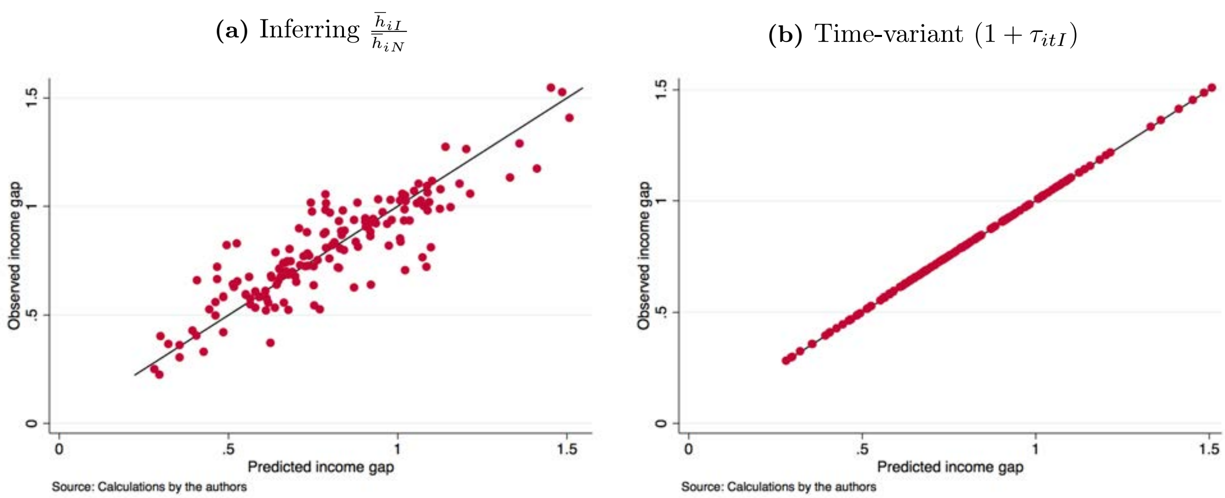
Notes: Figure shows in Panel A the averages over time of the inferred values of the group specific preferences, z_{igt}, which are normalized to $z_{1gt} = 1$, and in Panel B the averages of the productivities A_{igt}. Both measures use the baseline parameterization $\theta = 2.35$ and $\sigma = 3$.

Figure C.4 – Innate Talent Differences $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ in a Specification with Wedges Starting in 2017.



Notes: Figure shows the inferred permanent components of latent human capital of immigrants relative to natives $\frac{\overline{h}_{iI}}{\overline{h}_{iN}}$ in a specification where discriminatory wedges start in 2017 (whose results are reported in Column (2) of Table 5), and the average over occupations in the dashed line. The inference uses the baseline parameterization $\theta = 2.35$ and $\sigma = 3$.

Figure C.5 – Model Fit under Alternative Specifications



Notes: Figure shows in Panel A the model fit of , z_{igt}, which are normalized to $z_{1gt} = 1$, and in Panel B the averages of the productivities A_{igt}. Both measures use the baseline parameterization $\theta = 2.35$ and $\sigma = 3$.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