Labor Market Power, Firm Productivity, and the Immigrant-Native Pay Gap*

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Abstract

This paper examines the importance of labor market power and firm productivity for understanding the immigrant-native pay gap. Using matched employer-employee data covering the entire taxable population in Canada, I estimate an oligopsony model of the labor market with heterogeneous workers and firms. The results suggest that firms mark down wages by 23% for immigrants compared to 16% for natives and that immigrants sort into more productive firms. To decompose the immigrant-native pay gap, I use the model to conduct counterfactual experiments in a general equilibrium framework.

JEL Classification Numbers: J01, J15, J23, J31, J42

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1 Introduction

In all 33 high-income countries surveyed by the International Labour Organization of the United Nations, immigrants tend to earn less than native-born workers, with an average pay gap of 13% across countries (Amo-Agyei 2020). Canada, which has the highest proportion of immigrants among G7 countries, is no exception, despite having an immigration policy that is explicitly designed to attract high-skilled workers.[1] According to the 2016 Canadian Census, immigrants earn 16% less than natives on average, and this pay gap widens to 23% when controlling for education and experience.

The literature offers several explanations for the immigrant-native pay gap, including differences in language skills (Chiswick and Miller 1995), literacy (Ferrer, Green, and Riddell 2006), quality of schooling (Fortin, Lemieux, and Torres 2016), discrimination (Oreopoulos 2011), and job mobility (Pendakur and Woodcock 2010; Skuterud and Su 2012; Javdani and McGee 2018). Recent studies emphasize the role of employer wage-setting policies, using two-way fixed effects models in the Abowd, Kramarz, and Margolis (1999, hereafter AKM) tradition to estimate firm pay premia and assess their contribution to the pay gap. These studies show that immigrants are disproportionately employed in "low-wage firms," i.e., firms with relatively low pay premia (Damas de Matos 2017; Dostie et al. 2023; Arellano-Bover and San 2024; Amior and Stuhler 2024; Gyetvay and Keita 2024; Lehrer and Rawling 2025). However, firm pay premia arise from several distinct factors, including firm productivity, compensating differentials, and labor market power (Card et al. 2018), and we do not know the relative contribution of each. The existing literature provides little insight into the relative contribution of these factors due to the methodological challenges associated with measuring them and the substantial data requirements involved.

In this paper, I examine the importance of labor market power and firm productivity for

1. Due to recent record-breaking growth in immigration, roughly one-quarter of individuals in Canada are immigrants (Statistics Canada 2022). Moreover, a key feature of Canada's immigration policy is the point system that selects applicants with high levels of human capital (Beach, Green, and Worswick 2011).

understanding the immigrant-native pay gap. My empirical analysis uses the Canadian Employer-Employee Dynamics Database (CEEDD), a comprehensive matched employer-employee dataset that covers 100% of the taxable population in Canada. I estimate an oligopsony model of the labor market with heterogeneous workers and firms, and the results highlight two opposing forces. On the one hand, firms mark down wages by 23% for immigrants and 16% for natives on average, which increases inequality between the two groups. On the other hand, immigrants tend to sort into more productive firms, which decreases it. To decompose the immigrant-native pay gap, I conduct counterfactual exercises in which I eliminate specific sources of inequality—such as heterogeneity in firm productivity or labor supply—and solve for the pay gap that arises in the resulting counterfactual equilibrium. I assess each factor's contribution by comparing the counterfactual pay gap to the observed pay gap, thus incorporating general equilibrium responses of workers and firms into the decomposition analysis. There are three main takeaways. First, labor market power and differences in labor supply between immigrants and natives contribute to the pay gap. Second, heterogeneity in firm productivity lowers the pay gap, largely because immigrants are concentrated in cities where firms are more productive on average. Finally, the effect of labor supply heterogeneity on the pay gap depends on the distribution of firm productivity.

In Section 2, I provide an overview of Canada's immigration system. In Section 3, I describe the structural model, a novel application of the Chan et al. (2024, henceforth CKMM) framework. On the supply side, heterogeneous workers are divided into discrete types, each with multidimensional skills and preferences. I extend the CKMM framework by including immigrants in the worker-type classification. Workers have nested logit preferences over wages and amenities, and they choose their employer to maximize utility. Preferences for amenities are decomposed into *average* preferences, which are common to all workers of the same type, and *idiosyncratic* preferences, which vary across individuals. On the demand side, a finite number of heterogeneous firms produce using a technology in which worker types are perfect substitutes and each firm-worker type pair has its own match-specific productivity. Firms set wages to maximize profits, taking as given the labor supply of each worker type and the wages posted by other firms. In the Bertrand-Nash equilibrium, firms endogenously mark down wages below the marginal revenue product of labor (MRPL) due to strategic interactions in wage setting and lack of information about *idiosyncratic* preferences. To identify the structural model parameters, I follow CKMM closely. The key identifying assumption is that *average* preferences for amenities are fixed over time, which is a common assumption in the literature (e.g., Sorkin 2018; Lamadon, Mogstad, and Setzler 2022).

In Section 4, I describe the data used in the empirical analysis. The model is estimated using the CEEDD, a comprehensive longitudinal dataset of linked workers and firms derived from the tax system. The CEEDD covers the entire population of individuals and businesses with taxable income in Canada from 2002 to 2019. It is linked to the Immigrant Longitudinal Database (IMDB), an administrative dataset containing detailed demographic information on immigrants. An important feature of the CEEDD is the inclusion of firms' financial data, necessary to estimate labor demand.[2] To select the subset of individuals and firms for the analysis, I follow Dostie et al. (2023) and the AKM literature closely to obtain a sample of full-time equivalent (FTE) workers employed by firms in the private sector with at least two employees. Following Lamadon, Mogstad, and Setzler (2022), I define labor markets as combinations of two-digit industry codes and commuting zones.

In Section 5, I discuss the main estimates. The average firm-specific labor supply elasticity in Canada is 5.25, consistent with credible findings from other countries where firm-specific labor supply elasticities typically range between 3 and 6 (Card 2022; Manning 2021). This implies that firms mark down wages by 18% on average, meaning that workers earn 82% of their MRPL. Moreover, the estimates imply that immigrants' labor supply is more inelastic compared to natives, resulting in greater exposure to labor market power. Natives have an average firm-specific labor supply elasticity of 5.45, compared to 4.45 for immigrants. These

2. Other matched employer-employee datasets commonly used in studies of the immigrant-native pay gap, such as the German data (e.g., Amior and Stuhler 2024; Gyetvay and Keita 2024), lack financial information on firms.

estimates imply that firms mark down wages by 23% for immigrants and 16% for natives. In addition, there is notable heterogeneity across immigrant subgroups, with family immigrants and refugees having more inelastic labor supply compared to economic immigrants. The estimated labor supply elasticities imply that wages are marked down by 20% for economic immigrants, 25% for family immigrants, and 27% for refugees.

I also find that immigrants sort into firms with higher productivity on average. This result is striking, given that immigrants and natives tend to work at firms with similar revenue per worker. The structural model reconciles these patterns by revealing immigrants have lower productivity *within* firms on average, even though they sort into more productive firms. Furthermore, the finding that immigrants sort into higher-productivity firms may be surprising given the AKM literature cited above, which finds that immigrants tend to work at firms with lower reduced-form pay premia. The structural model reveals that the AKM firm pay premia mask two opposing forces: firm productivity, which raises immigrants' relative wages, and labor market power, which lowers them.

Additional findings discussed in Section 5 shed light on the sources of immigrants' increased exposure to labor market power. First, firms that employ a greater share of the labor market mark down wages further below the MRPL. This finding motivates an investigation into whether immigrants are differentially exposed to labor market concentration as a way to understand their increased exposure to labor market power. Using a generalized concentration index (GCI), I find that immigrants are indeed more exposed to labor market concentration relative to natives. This result may appear counterintuitive in the Canadian context, where immigrants disproportionately reside in large cities that have many firms with relatively small individual labor market shares.[3] To investigate this discrepancy, I decompose the GCI into within- and between-market components. I find that immigrants face lower concentration *within* labor markets but higher concentration *between* labor markets. The

3. Although around one quarter of all individuals are immigrants in Canada, more than 50% live in Toronto, Vancouver, or Montreal.

between-market component dominates the within-market component, resulting in greater overall exposure to labor market concentration for immigrants.

Second, estimates of the labor supply parameters indicate that jobs are more horizontally differentiated for immigrants, causing immigrants' firm-specific labor supply to be more inelastic. I interpret this as evidence that immigrants have fewer *suitable* job options, in the sense that fewer matches are actually feasible, even within labor markets that contain many firms. This channel operates alongside labor market concentration as a complementary source of increased exposure to labor market power for immigrants.

In Section 6, I discuss the counterfactual analyses used to explore the determinants of the immigrant-native pay gap. Each counterfactual analysis proceeds as follows. First, I select a subset of model parameters to manipulate in the counterfactual, such as the utility parameters that govern labor supply or the technology parameters that influence firm productivity. Next, I eliminate differences in the selected model parameters across immigrants and natives by setting these parameters equal to a common value (typically the mean or median in the data). Then, I predict the effects on wages and employment by solving for the counterfactual equilibrium. Importantly, this approach incorporates general equilibrium responses, including adjustments in wage markdowns, marginal revenue products of labor, and the allocation of workers across firms. Finally, I summarize the results by reporting the *counterfactual* immigrant-native pay gap and comparing it to the *observed* immigrant-native pay gap. This approach allows me to decompose the pay gap, isolating the contribution of the selected model parameters from the combined effect of all other factors.

There are three main takeaways from the counterfactual analyses. First, a significant portion of the immigrant-native pay gap is driven by differences in labor supply between immigrants and natives, as well as firms' labor market power which allows them to exploit these differences. I demonstrate this in a counterfactual experiment in which immigrants and natives have the same distribution of idiosyncratic preferences for firm non-wage amenities. These preferences govern the shape of the labor supply curves because they reflect how substitutable workers perceive firms to be. In this counterfactual scenario, the immigrant-native pay gap falls significantly, illustrating the importance of differences in labor supply and labor market power for the pay gap.

Second, heterogeneity in firm productivity reduces the earnings inequality between immigrants and natives. I demonstrate this using a counterfactual experiment in which all firms have the same total factor productivity (TFP) and returns to scale. In this counterfactual, the immigrant-native pay gap rises. This striking result is driven by the tendency for immigrants to work in cities where firms are more productive on average. I show this using a subsequent counterfactual experiment in which I eliminate heterogeneity in TFP and returns to scale *within* cities while maintaining heterogeneity in these parameters *across* cities. In this subsequent counterfactual experiment, the immigrant-native pay gap decreases. This suggests that immigrants tend to sort into cities with more productive firms compared to natives, but within the same city, immigrants tend to work at less productive firms.

Finally, the contribution of labor supply differences to the pay gap depends on the distribution of firm productivity. If we equalize the distribution of idiosyncratic preferences for amenities across immigrants and natives (while maintaining heterogeneity in all other parameters), the pay gap decreases by approximately 15 percentage points. However, if we first eliminate TFP differences across firms, the same adjustment to preferences reduces the gap by only 4 percentage points. This demonstrates that heterogeneity in firm productivity magnifies the contribution of labor supply differences and shows that interactions between firm productivity and labor supply contribute to the pay gap.

In addition to the literature on earnings inequality between immigrants and natives discussed earlier, my paper contributes to the growing literature on monopsony power and immigration (Amior and Manning 2020; Naidu, Nyarko, and Wang 2016; Depew, Norlander, and Sorensen 2017; Hunt and Xie 2019; Wang 2021; Hirsch and Jahn 2015; Kroft et al. 2025). A particularly relevant study is Kroft et al. (2025), which studies earnings inequality between temporary foreign workers (TFWs) and natives using the CEEDD. My paper complements Kroft et al. (2025) by focusing exclusively on the pay gap between native-born workers and immigrants who are or have been permanent residents. Another particularly relevant study is Hirsch and Jahn (2015), which applies the dynamic monopsony framework of Manning (2003) to measure labor supply elasticities and wage markdowns for immigrants and natives in Germany. My estimate of the immigrant-native markdown gap—approximately 7 percentage points—aligns with the 7.7 log point gap found in Hirsch and Jahn (2015). Relative to Hirsch and Jahn (2015), my paper advances the literature in two key ways. First, it examines not only the importance of labor market power, but also the importance of firm productivity and its interaction with heterogeneity in labor supply. Second, it decomposes the pay gap using counterfactual experiments in a general equilibrium framework—an approach that, to my knowledge, has not been explored in the existing literature.

2 Immigration in Canada

Foreign-born individuals living in Canada may hold temporary resident status, permanent resident status, or citizenship. Permanent residents have the right to live, work, and study in Canada indefinitely; the only difference between permanent residency and citizenship is a limited set of additional rights, including eligibility to run for political office and hold certain jobs requiring high-level security clearance. Individuals are granted permanent residence through one of three admission classes: the *Economic Class*, the *Family Class*, or the *Refugee and Humanitarian Class*.

The *Economic Class* grants permanent residence to individuals primarily on the basis of their human capital characteristics. This class encompasses a range of federal and subnational programs designed to select high-skilled immigrants. For example, the *Federal Skilled Workers Program (FSWP)* introduced in 1967 assigns points to applicants based on their age, education, experience, and language proficiency, and applicants with points above a minimum threshold meet the program's selection criteria. At the subnational level, the *Provincial Nominee Program (PNP)* allows participating provinces and territories to design their own immigration streams based on local economic needs. PNP streams typically focus on selecting immigrants who work in high-demand occupations or have a job offer from an employer within the province.[4] For additional details on the federal and provincial programs within the *Economic Class*, see Appendix B.

The *Family Class* was introduced in 1976 as an admission category for applicants who have family members who are Canadian citizens or permanent residents. Through the *Family Class*, permanent residents or citizens of Canada can sponsor other family members, including spouses, dependents, and parents, and must commit to financially supporting sponsored relatives for several years. For applicants who intend to reside in Quebec, the process includes an additional step in which the Quebec government must approve the sponsor.

The *Refugee and Humanitarian Class* grants permanent residence to individuals based on need for protection. It was formally introduced with the *Immigration Act* of 1976, which made refugee protection a permanent part of Canada's immigration system. Individuals are selected on humanitarian grounds when they face serious risks such as persecution, violence, or hardship in their home country, or when exceptional compassionate circumstances apply. Refugees receive additional support from the federal government compared to other immigrants when they first arrive in Canada, including income assistance, housing help, and settlement services.

The three admission classes discussed above are only available for permanent residents. Foreign-born individuals who are living or working in Canada and do not have citizenship or permanent residency status must have temporary resident status. Temporary residents are

4. The province of Quebec has its own program that is distinct from the PNP and evaluates applicants using a points-based system similar to the FSWP, although with additional emphasis on French language proficiency.

given the right to live, work, or study in Canada for a limited time only and include international students, temporary foreign workers (TFWs) with employer-specific visas admitted under the *Temporary Foreign Worker Program (TFWP)*, and other TFWs with open work permits admitted through the *International Mobility Program (IMP)*. Due to the unique legal restrictions associated with temporary visas, I exclude temporary residents from my analysis. For an analysis of earnings inequality between TFWs and permanent residents, see Kroft et al. (2025).

3 Model

3.1 Set up

Heterogeneous workers are categorized into discrete types, and each worker i has type $k \in \mathcal{K}$. I extend the CKMM framework by including immigrants in the worker-type classification. As explained in Section 2, there are three main admission categories for permanent residency in Canada: the Economic Class, the Family Class, and the Humanitarian and Refugee Class. These admission categories may reflect differences in skills or labor supply behavior, and as a result I include these in the worker type classification. TFWs are excluded from the analysis entirely due to the distinct legal restrictions associated with temporary permits. Consistent with labor market power and gender pay gap literature (Sharma 2024; Robinson 1933; Webber 2016), workers are also classified by gender. Finally, to account for heterogeneous returns to education and experience by country of origin (Fortin, Lemieux, and Torres 2016), workers are grouped by continent (Europe, Africa, Asia, Americas), and I adopt the specific grouping rules from Dostie et al. (2023) (e.g., U.S., Australia, and New Zealand are grouped with Europe; Mexico is grouped with the Americas).

There are M_t workers in the economy at time t, and m_{kt} workers of each type, with $\sum_{k=1}^{K} m_{kt} = M_t$. There are $g \in \mathcal{G}$ local labor markets in the economy, where each local labor market is defined by location, i.e., Census Metropolitan Area (CMA) or Census Agglomeration (CA), and industry (2-digit NAICS code). Additionally, there are J firms in the economy indexed by $j \in \mathcal{J}$. Let $\mathcal{J}_g$ denote the set of firms in local labor market g.

3.2 Labor Supply

Workers are heterogeneous in their preferences over firms. The indirect utility of employment at firm j at time t for worker i of type k is given by:

$$U_{ijt} = \beta_k \log w_{kjt} + \log u_{kjt} + \varepsilon_{ijt}, \tag{1}$$

where w_{kjt} is the wage offered by firm j to worker type k at time t, $\log u_{kjt}$ represents the *average* preference for amenities at firm j common to all workers of type k at time t, and ε_{ijt} captures the *idiosyncratic* preference over amenities at firm j at time t specific to worker i. The outside option in the model is non-employment, denoted as $j = 0$, with benefits w_{k0t}. The value of the outside option is normalized to zero, i.e., $\log(u_{k0t}) = 0$. Define $v_{kjt} \equiv \beta_k \log w_{kjt} + \log u_{kjt}$.

In each period t, the *idiosyncratic* preference ε_{ijt} is assumed to follow a nested logit distribution with distribution function:

$$F(\vec{\varepsilon}_{it}) = \exp\left\{ \sum_{g\in\mathcal{G}} \sum_{j\in\mathcal{J}_g} \left[\exp\left(-\sigma_{kg}\varepsilon_{ijt}\right)\right]^{\frac{1}{\sigma_{kg}}} \right\}, \tag{2}$$

where $\frac{1}{\sigma_{kg}} = \sqrt{1 - \mathrm{corr}(\varepsilon_{ijt}, \varepsilon_{ij't})}$ for $j, j' \in \mathcal{J}_g$. The parameter σ_{kg} measures the correlation of the *idiosyncratic* preferences for firms within the same market.

This utility specification allows for firms to be imperfect substitutes, creating "job differentiation." There are two dimensions of job differentiation in the model: vertical differentiation, captured by variation in $\log(u_{kjt})$, and horizontal differentiation, captured by variation in ε_{ijt}. Both vertical and horizontal differentiation generate labor market power, although the mechanism is different in each case. Firms with high u_{kjt} will attract more workers, implying a greater labor market share and more labor market power. When firms are horizontally differentiated, workers have fewer *suitable* job options, in the sense that fewer worker-firm matches are actually viable. Horizontal differentiation generates labor market power, even within labor markets that have many firms.

The degree of horizontal differentiation for workers of type k in labor market g is governed by the parameters σ_{kg} and β_k.[5] If $\sigma_{kg} = 1$, idiosyncratic preference shocks within the same labor market are independent, whereas if $\sigma_{kg} = \infty$, idiosyncratic preference shocks are perfectly correlated within a labor market and firms within the same labor market are viewed as perfect substitutes. The parameter β_k represents the marginal utility of wages.

In the model, workers choose the firm that provides the highest utility. Let $L^s_{kjt}(w_{kjt})$ denote the labor supply function for type k workers at firm j at time t. Following McFadden (1978), the labor supply function can be expressed as:

$$L^s_{kjt}(w_{kjt}) = m_{kt} \frac{\partial G_{k.}(v_{k.t})}{\partial v_{kjt}}, \tag{3}$$

where

$$G_{k.}(v_{k.t}) \equiv \mathbb{E}\left[\max_{j \in \mathcal{J} \cup \{0\}} \{v_{kjt} + \varepsilon_{ijt}\}\right]$$

is the expected utility from the decision problem. Assuming that ε_{ijt} follows the nested logit structure described in Equation (2), the expression for $G_{k.}(v_{k.t})$ is:

$$G_{k.}(v_{k.t}) = \log\left\{ e^{v_{k0t}} + \sum_{g \in \mathcal{G}} \left(\sum_{j \in \mathcal{J}_g} e^{v_{kjt}\sigma_{kg}} \right)^{1/\sigma_{kg}} \right\}. \tag{4}$$

5. When estimating the model, I restrict heterogeneity in the σ_{kg} parameter so that it is assumed to be constant within each unique combination of worker type and province group (Ontario, Quebec, British Columbia, and all other provinces). However, note that the nested logit structure assumes that idiosyncratic preference shocks are correlated within each *local labor market*, even though the heterogeneity in the σ_{kg} parameter only varies across provinces.

The derivative of $G_{k.}(v_{k.t})$ with respect to v_{kjt} can be calculated using Equation (4). Substituting it into Equation (3) provides the supply of type-k workers to firm j at time t.

Following CKMM and Berry (1994), the empirical analysis uses the *quasi*-supply function, defined as the supply of type-k workers to firm j *relative* to non-employment:

$$\log \frac{s_{kjt}}{s_{k0t}} = \beta_k \log \frac{w_{kjt}}{w_{k0t}} + (1 - 1/\sigma_{kg}) \log s_{kjt|g} + \log u_{kjt}, \tag{5}$$

where s_{kjt} is the share of type-k workers at firm j in period t, w_{kjt} is the wage paid to type-k workers by firm j in period t, s_{k0t} is the share of non-employed type-k workers in period t, w_{k0t} is the non-employment benefits for type-k workers in period t, and $s_{kjt|g}$ is firm j's share of type-k workers in labor market g who are employed by firm j in period t (the "labor market share").

It is possible to express the firm-specific labor supply elasticity as:

$$\mathcal{E}_{kjt} = \beta_k \sigma_{kg} + \beta_k [(1 - \sigma_{kg}) s_{kjt|g} - s_{kjt}]. \tag{6}$$

Equation (6) shows that the firm-specific labor supply elasticity is a function of β_k, σ_{kg}, $s_{kjt|g}$, and s_{kjt}. The expression shows that when there is more horizontal differentiation, i.e., β_k and σ_{kg} are lower, the firm-specific labor supply is more inelastic, i.e., $\mathcal{E}_{kjt}$ is lower. Since $1 - \sigma_{kg} < 0$, Equation (6) also shows that the firm-specific labor supply is more inelastic when firms have a greater labor market share.

3.3 Labor Demand

The demand side of the model is characterized by a wage-posting framework with heterogeneous firms. The labor input of worker type k at firm j at time t is denoted l_{kjt}, and $l_{.jt} \equiv (l_{1jt}, \ldots, l_{Kjt})$ is the vector of labor inputs at firm j at time t. Let $F_{jt}(l_{.jt})$ be the production function for firm j at time t, and let $C_{jt} \subset \mathcal{K}$ denote the set of worker types employed by firm j at time t. Assume firm j at time t has the following production technology:

$$F_{jt}(l_{\cdot jt}) = \left(\sum_{k \in C_{jt}} \tilde{\gamma}_{kjt} l_{kjt} \right)^{\alpha_{jt}}, \tag{7}$$

where $\tilde{\gamma}_{kjt} \equiv \theta_{jt}\gamma_{kjt}$ and $\sum_{k \in C_{jt}} \gamma_{kjt} = 1$. The parameter $\tilde{\theta}_{jt} \equiv \theta_{jt}^{\alpha_{jt}}$ is the TFP of firm j in period t, the parameter α_{jt} is the returns to scale of firm j in period t, and the parameter γ_{kjt} is the match-specific productivity of type-k workers at firm j in period t.[6]

This production technology allows for substantial heterogeneity in productivity across periods, firms, and different worker types. The match-specific productivity is allowed to be different for each firm-worker type pair, generating Roy sorting (Roy 1951). The production technology implies that workers are perfect substitutes, following Lamadon, Mogstad, and Setzler (2022). This assumption is common in the monopsony literature, and CKMM test for imperfect substitution among different worker types and find that a perfect-substitutes production function approximates the production process well.

In the model, firms post a vector of type-specific wages that maximize profits each period, treating their firm-specific labor supply curve and the posted wages of other firms as given.[7] Formally, in period t, firm j chooses the vector of wages $\vec{w}_{jt}$ to maximize

$$P_{jt}F_{jt}(l_{\cdot jt}) - \sum_{k \in \mathcal{K}} w_{kjt} l_{kjt},$$

subject to the type-specific labor supply curves $l_{kjt} = L^s_{kjt}(w_{kjt})$ and the vector of posted wages of other firms $\vec{w}_{-j,t}$.

The first-order condition (FOC) for profit maximization can be rearranged as follows:

6. We can re-arrange Equation (7) to obtain $F_{jt}(l_{\cdot jt}) = \theta_{jt}^{\alpha_{jt}} \left(\sum_{k \in C_{jt}} \gamma_{kjt} l_{kjt} \right)^{\alpha_{jt}}$, which shows that a natural interpretation of $\tilde{\theta}_{jt} \equiv \theta_{jt}^{\alpha_{jt}}$ is total factor productivity (TFP).

7. There is a unique equilibrium wage vector in the Bertrand-Nash equilibrium.

$$w_{kjt} = \underbrace{P_{jt}\frac{\partial F_{jt}(l_{\cdot jt})}{\partial l_{kjt}}}_{\text{MRPL}_{kjt}} \times \frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}, \tag{8}$$

where

$$\mathcal{E}_{kjt} = \frac{\partial l_{kjt}}{\partial w_{kjt}} \frac{w_{kjt}}{l_{kjt}}$$

represents the firm-specific labor supply elasticity of type-k workers to firm j in period t and the term MRPL_{kjt} is the marginal revenue product of labor. We can re-arrange this equation to express the wage markdown as a function of the firm-specific labor supply elasticity:

$$\underbrace{\frac{\text{MRPL}_{kjt} - w_{kjt}}{\text{MRPL}_{kjt}}}_{\text{Wage Markdown}} = \frac{1}{1+\mathcal{E}_{kjt}}. \tag{9}$$

3.4 Identification

To identify the structural model parameters, I follow CKMM closely. Below, I provide an intuitive overview of the identification approach; a detailed description is available in Appendix C.

The quasi-supply function (Equation (5)) is used to identify the labor supply parameters. The quasi-supply function directly controls for the firm's labor market share to account for strategic interactions in wage setting. The remaining identification problem is that the *average* preferences for amenities may be correlated with the wage or labor market share. To overcome this identification challenge, an instrumental variables (IV) approach is used, where "short changes" in variables that proxy for firm productivity are used as instruments for "long changes" in earnings and labor market shares. The key identifying assumption of this "internal panel instruments" approach is the assumption that each worker type's *average* preferences for amenities are fixed over time.[8] This assumption is common in the literature;

8. It is also possible to invoke a weaker assumption that the average preferences for amenities are *transitory*, although I adopt the assumption that average preferences are fixed because it is consistent with the literature

see Sorkin (2018) or Lamadon, Mogstad, and Setzler (2022) for some well-known examples. Two-stage Least Squares (2SLS) is used to estimate Equation (5) in practice.

To identify the production technology parameters, the first order condition for profit maximization is used. Within-firm productivity is identified (up to a normalization) by comparing the relative MRPL across worker types within the same firm. The returns to scale parameter, which captures curvature in the production function, is identified by comparing a linear approximation to revenue calculated using labor inputs to the observed revenue in the data. Finally, TFP is identified as the residual that equates the observed revenue to the revenue implied by the production function.

4 Data

To estimate the model, I use data from the Canadian Employer-Employee Dynamics Database (CEEDD), a comprehensive matched employer-employee dataset maintained by Statistics Canada. The CEEDD covers the near universe of individuals and firms in Canada from 2002 to 2019. This dataset integrates several sources: the T1 personal master file (T1PMF), which provides demographic information such as age, location, marital status, and gender; the T4 database linked to the record of employment (T4ROE), which includes job-level data on earnings and industry; the National Accounts Longitudinal Microdata File (NALMF), which contains details on firms' financial positions; and the Immigrant Longitudinal Database (IMDB), which offers rich demographic information on immigrants, including country of origin and admission class.

Data cleaning closely follows the methodology outlined in Dostie et al. (2023) and Li, Dostie, and Simard-Duplain (2023), who both estimate an AKM model using the CEEDD. I follow these papers closely so that my results speak directly to the literature on firm-specific pay premia and their role in the immigrant-native earnings gap.

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and easier to interpret.

I obtain information on immigrant status from the IMDB, classifying individuals as permanent residents in all years after their landing year. I do not distinguish between those who later became Canadian citizens and those who remain permanent residents, as there is very little difference between citizenship and permanent residency (see Section 2). Individuals with missing marital status, those who do not identify as male or female, and those outside the working age of 25 to 59 are excluded. Furthermore, the sample is limited to individuals whose employment income is at least as large as their self-employment income, where self-employment income includes earnings from business, farming, fishing, rental, commissions, and professional activities. I also exclude TFWs because temporary visas are typically associated with unique legal restrictions that require a separate analysis (see Section 2).

Firms in the public sector (NAICS 91), education (NAICS 61), and health sectors (NAICS 62) are excluded. The sample is also restricted to incorporated firms that meet several criteria: they must have at least $50,000 in revenue, at least $100 in value added per worker, and revenue that is at least as large as the total wage bill. Additionally, these firms must have at least two employees, where employment is defined as the average of all non-zero monthly employment submissions from the PD7.

Since the CEEDD derives its data from tax records, it lacks information on hours worked. To address this, the sample is restricted to full-time equivalent (FTE) workers, defined as those earning at least approximately $18,000 in 2012 dollars following Li, Dostie, and Simard-Duplain (2023).[9] Moreover, individuals in the CEEDD may have multiple T4 records if they hold multiple jobs. I restrict the data to each individual's primary job, defined as the job that provides the highest earnings in any given year.

Labor markets are defined following Lamadon, Mogstad, and Setzler (2022) as combinations of two-digit NAICS codes and geographic locations. Geographic locations are based on

9. This FTE threshold is calculated by multiplying the minimum wage by an average full-time work schedule of 38.8 hours per week over 48 weeks. It represents what an individual would earn if they work full-time all year at the minimum wage (Li, Dostie, and Simard-Duplain 2023).

Census Metropolitan Areas (CMAs) or Census Agglomerations (CAs) as defined in the 2016 Census. CMAs and CAs consist of population centers and adjacent municipalities with high commuting flows, resembling commuting zones in the United States. Labor markets in the territories (Yukon, Northwest Territories, and Nunavut) are excluded from the analysis.

In the CEEDD, both worker and firm locations are available. Worker location is derived from the T1PMF, while firm location comes from the NALMF. However, firms in the CEEDD are defined by their Enterprise ID in the Business Registry for tax purposes, which means location data reflect the headquarters' location. For multi-location firms, each firm-location pair is treated as an independent unit with distinct production technologies, where the locations correspond to the locations of the firm's workers. To measure revenue at each of these units, I allocate firm-level revenue associated with the Enterprise ID according to each unit's share of total wage bill, following CKMM. (Note, however, that I use the Enterprise ID revenue as an instrument in the estimation; see Appendix C.)

The summary statistics for the estimation sample are quite similar to Dostie et al. (2023), as shown in Table 1. We see that immigrants tend to work at firms that are larger, both in terms of total revenue and number of employees. However, the average revenue per worker of an individual's employer is similar for both immigrants and natives. We also see that there is a significant amount of segregation between immigrants and natives. For immigrants, on average roughly 51% of coworkers are immigrants, whereas for natives, this share is only 11%. Additionally, although the vast majority of immigrants tend to work at firms that hire both immigrants and natives (90%), roughly 40% of natives work at firms that *only* hire natives. Finally, we see that there is a pay gap within firms that hire both immigrants and natives and among firms that hire *only* natives or *only* immigrants.

To mitigate the influence of outliers, earnings and revenue are winsorized at the 0.5% and 99.5% percentiles prior to estimation.

5 Results

In this section, I discuss employment-weighted averages of model parameters across immigrants and natives (and various subgroups of immigrants). Precisely, for any subset of worker types $\mathcal{S} \subset \mathcal{K}$ (for example, $\mathcal{S}$ could be the subset of k such that k is an immigrant), define the average value of some parameter x_{kjt} as

$$\overline{x}_{k\in\mathcal{S}} \equiv \sum_{j\in\mathcal{J}} \sum_{t=2002}^{2019} \sum_{k\in\mathcal{S}} \omega_{kjt} x_{kjt},$$

where $\omega_{kjt} = \frac{l_{kjt}}{\sum_{j\in\mathcal{J}} \sum_{t=2002}^{2019} \sum_{k\in\mathcal{S}} l_{kjt}}$ are the weights equal to the share of total type-k workers in the data at firm j at time t.

5.1 Labor Supply

Before discussing the main results, I begin by discussing the relevance condition associated with the IV approach used to estimate the labor supply parameters. As discussed in Appendix C, the relevance condition of the IV is the persistence of firm productivity shocks. The first stage results presented in Table A1 indicate that the relevance condition holds: the short changes in variables that proxy for productivity are strongly correlated with long changes in the earnings and labor market shares.

The main estimates of the labor supply parameters indicate that the distributions of idiosyncratic preferences for amenities differ between immigrants and natives. Table A2 presents employment-weighted averages of the estimated labor supply parameters β_k and σ_{kg} for immigrants and natives, with 95% confidence intervals calculated using the bootstrap estimator from Hall (1992).[10] We find that immigrants have a higher average β_k (0.70) compared to natives (0.56), and this difference is statistically significant at the 5% level. Conversely, immigrants have a lower average σ_{kg} (6.81), compared to natives (11.73), and this difference is

10. Confidence intervals can be asymmetric if the underlying distribution is asymmetric, and this is indeed the case for many of the estimated parameters.

also statistically significant at the 5% level. The lower σ_{kg} for immigrants suggests that they have fewer job alternatives within the same labor market compared to natives, i.e., natives are more likely to find an alternative job within the same market that is a close substitute to their current employment. Figure A1 displays the values of β_k and Figure A2 displays the average σ_{kg} for each k-group.

Given the labor supply parameters β_k and σ_{kg}, we can calculate firm-specific labor supply elasticities using Equation (6). The results suggest a considerable amount of labor market power in Canada, with the average firm-specific labor supply elasticity across all workers equal to 5.25 and the 95% confidence interval ranging from 5.16 to 5.46. This estimate is similar to credible estimates of firm-specific labor supply elasticities in the literature that typically range between 3 and 6 (Card 2022; Sokolova and Sorensen 2021; Manning 2021). The results also suggest that immigrants' labor supply is more inelastic compared to natives. Figure 1 shows that the average firm-specific labor supply elasticity for immigrants (4.42) is lower and statistically different at the 5% level from the average firm-specific labor supply elasticity for natives (5.45).

Figure 2 shows heterogeneity in labor supply elasticities across admission categories, with economic immigrants having the highest firm-specific labor supply elasticity (5.09), followed by family immigrants (3.85) and refugees (3.20). All three of these estimates are statistically significant from each other at the 5% level, although the 95% confidence interval for the average firm-specific labor supply elasticity for economic immigrants overlaps with the 95% confidence interval for the average firm-specific labor supply elasticity for natives. Figure A3 displays the firm-specific labor supply elasticities for each k-group.[11]

11. Native-born men have an average labor supply elasticity of 5.64, which is higher than and statistically different at the 5% level from the average labor supply elasticity of 5.09 for native-born women. This suggests that labor market power matters for the gender pay gap, consistent with the recent literature (Sharma 2024; Webber 2016) and the seminal hypothesis of Robinson (1933). Additionally, certain highly skilled immigrant groups, such as those from Europe, exhibit notably low elasticities. This result reflects the horizontally differentiated labor markets they participate in, as indicated by their low β_k and average σ_{kg} in Figures A1 and A2.

Using the model, we can translate these elasticities into markdowns to quantify the effect of labor market power on wages using Equation (9). The results suggest that firms mark down wages by 18% for all workers in Canada on average, with a 95% confidence interval ranging from 18% to 17%. These estimates imply that workers receive 82% of their marginal revenue product of labor (MRPL). Moreover, in Figure 1, we see that there is heterogeneity across immigrant status, with firms marking down native wages by 18% and immigrant wages by 23% on average, and this difference is statistically significant at the 5% level. These results imply that natives earn 84% of their MRPL, compared to immigrants who earn 77%. These estimates are in line with Hirsch and Jahn (2015), who find that the gap in markdowns between immigrants and natives is roughly 7.7 log points.

Turning to heterogeneity by immigration category, Figure 2 shows that firms mark down wages by 20% for economic immigrants, 25% for family immigrants, and 27% for refugees, and these estimates are all statistically different from each other at the 5% level. These estimates imply that economic immigrants earn 80% of their MRPL, family immigrants earn 75%, and refugees earn 73%. Figure A4 displays the markdowns for each k-group and Appendix E.1 discusses some heterogeneity in markdowns across Canadian provinces.

5.2 Labor Demand

We turn now to estimates of the labor demand parameters, which can be categorized into two groups: the "firm productivity" parameters α_{jt} and $\tilde{\theta}_{jt}$ (which vary at the firm level and are the same for all workers at the same firm), and the "match-specific" parameters γ_{kjt} (which vary across worker types within the same firm).

First, we examine the firm productivity parameters. The average value of the returns to scale parameter α_{jt} across the full sample is 0.26, with both the upper and lower bounds of the 95% confidence interval equal to 0.26 (rounded to two decimal places). These results indicate generally decreasing returns to scale for firms, similar to the findings in CKMM and

Lamadon, Mogstad, and Setzler (2022). Comparing immigrants and natives, we find that the firm productivity parameters tend to be slightly higher for immigrants, a result that is entirely due to sorting across firms. Figure 3 shows that immigrants have an average α_{jt} of 0.27, compared to 0.25 for natives, and this difference is statistically significant at the 5% level. The average $\log \tilde{\theta}_{jt}$ is higher for immigrants on average (16.54) compared to natives (15.85), and this difference is also statistically significant at the 5% level.

There are also interesting patterns in TFP across different subgroups. As shown in Figure 4, we see that economic immigrants sort into firms with the highest TFP on average, followed by natives, refugees, and family immigrants. This result is interesting, as it shows that part of the wage premium earned by economic immigrants is due to sorting across firms (not just higher human capital). Figure A6 displays the average α_{jt} and Figure A7 displays the average $\log(\tilde{\theta}_{jt})$ for each k-group.

The match-specific parameters γ_{kjt} are normalized to sum to 1 for every firm in every period, i.e., $\sum_{k \in C_{jt}} \gamma_{kjt} = 1$. This normalization complicates direct comparisons of γ_{kjt} across worker types. To explore differences in match-specific productivity between immigrants and natives, I estimate the following regression:

$$\log(\hat{\gamma}_{kjt}) = \Gamma_k + \psi_{jt} + e^{\gamma}_{kjt}, \tag{10}$$

where $\hat{\gamma}_{kjt}$ are the estimated match-specific productivity parameters, Γ_k are worker-type fixed effects (female natives are the omitted category), ψ_{jt} are firm-by-year fixed effects, and e^{γ}_{kjt} is the error term. In Figure 3, I calculate the employment-weighted average Γ_k across immigrants and natives and find that immigrants tend to have lower match-specific productivity. The results for each Γ_k are reported in Figure A8.

The finding that immigrants tend to work at more productive firms is striking, especially given the summary statistics presented in Table 1. On the one hand, we see in Table 1 that immigrants tend to work at larger firms with more revenue and more employees, suggesting that immigrants work at firms that are more productive on average. However, the revenue per worker of the employer is similar for immigrants and natives. The structural model reconciles these patterns by revealing that although immigrants sort into firms with higher firm productivity, they tend to have lower match-specific productivity within the same firm. In addition, the results that immigrants work at more productive firms may be surprising given the literature on firm pay premia, which suggests that immigrants work at low-premium firms. However, the structural model shows that the reduced-form pay premia mask two opposing forces: labor market power, which increases the pay gap, and firm productivity, which lowers it.

5.3 Sources of Labor Market Power

5.3.1 Labor Market Concentration

To investigate the source of immigrants' increased exposure to labor market power, I first begin by examining how labor market power varies with the firm's labor market share. Figure 5 shows that firms with larger labor market shares face more inelastic labor supply and set wages further below the MRPL. This pattern holds for both immigrants and natives.

This motivates examining whether immigrants are employed by firms with higher labor market shares on average, i.e., whether immigrants tend to work in labor markets that are more highly concentrated. To investigate this, I use the generalized concentration index (GCI) proposed in CKMM to analyze immigrants' and natives' exposure to labor market concentration. The GCI has the form:

$$GCI_{kt} \equiv \underbrace{\left[\prod_{g\in\mathcal{G}}\left(\exp\left\{\sum_{j\in\mathcal{J}_g} s_{kjt|g}\log s_{kjt|g}\right\}\right)^{\frac{s_{kgt}}{\sigma_{kg}}}\right]}_{\text{Within-group concentration index (WGCI)}} \times \underbrace{\left[\exp\left\{\sum_{g\in\mathcal{G}} s_{kgt}\log s_{kgt}\right\}\right]}_{\text{Between-group concentration index (BGCI)}},$$

where $s_{kjt|g}$ is firm j's share of employment of type-k workers in market g at time t, and s_{kgt} is the share of total workers of type k who are employed in market g at time t. The GCI can be decomposed into within- and between-market components. The within-group concentration index (WGCI) captures the extent to which type-k workers are exposed to labor market concentration *within* labor markets, while the between-group concentration index (BGCI) measures the concentration of type-k workers *between* labor markets. If type-k workers primarily work in a small number of labor markets, their BGCI will be higher, regardless of how many firms operate within those labor markets and those firm's labor market shares. In contrast, the WGCI is more closely related to the commonly used Herfindahl-Hirschman Index (HHI) and will be higher if the type-k workers are employed in labor markets that have a small number of firms, each with relatively high labor market shares.[12]

Figure 6 shows that immigrants are exposed to greater labor market concentration than natives, as evidenced by a higher average GCI. This difference is driven by substantially higher BGCI for immigrants, while their WGCI is lower. In Canada, immigrants disproportionately reside in the three largest cities (Toronto, Montreal, and Vancouver). These cities contain many firms, each with relatively small labor market shares compared to firms in smaller cities or more rural regions. Thus, immigrant sorting into larger cities leads to lower WGCI for them on average. At the same time, immigrants are highly concentrated geographically. For example, although immigrants comprise roughly one quarter of the Canadian population, more than half live in the three largest cities. This spatial clustering increases between-market concentration, which is reflected in the higher BGCI. Overall, the higher BGCI more than offsets the lower WGCI, resulting in immigrants facing greater overall labor market concentration than natives.

12. CKMM show that in the nested logit model, a higher GCI implies lower welfare, implying that the GCI has a direct welfare interpretation. The widely used Herfindahl-Hirschman Index (HHI) is not linked to welfare in the same way. Moreover, the HHI lacks a "between-market" component.

5.3.2 Horizontal Differentiation

The estimates of the labor supply parameters described in Section 5.1 suggest that jobs are more horizontally differentiated for immigrants compared to natives. Figure 5 demonstrates how more horizontal differentiation translates into increased exposure to labor market power for immigrants. It shows that, even conditional on labor market share, labor supply to the firm is more inelastic for immigrants compared to natives, causing firms to mark down immigrant wages more.

I interpret these results as evidence that immigrants have fewer *suitable* job options. That is, even in labor markets with many firms, fewer matches are viable for immigrants relative to natives. This channel operates alongside labor market concentration as a complementary source of increased exposure to labor market power for immigrants.

The methodology in this paper is not well-suited to identify the specific factors that increase horizontal differentiation for immigrants relative to natives; the analysis simply points to horizontal differentiation as an important driver of immigrants' increased exposure to labor market power. I leave the analysis of the underlying mechanisms that generate increased horizontal differentiation for immigrants as a promising avenue for future research.

5.4 Determinants of Labor Supply Heterogeneity

The above discussion shows that immigrants are concentrated geographically, giving rise to increased exposure to labor market concentration and labor market power. Additionally, we have seen that within labor markets, increased horizontal differentiation for immigrants reduces the number of matches that are actually feasible for immigrants compared to natives. Both these results point to the importance of labor supply heterogeneity between immigrants and natives as an important contributor to the immigrant-native pay gap. In this section, I use the model to gain insight into the determinants of labor supply heterogeneity by investigating which observable employer characteristics are correlated with labor supply.

Using the estimates of β_k and σ_{kg}, it is possible to use Equation (5) to estimate type-k workers' *average* preferences for amenities at firm j in period t:

$$\widehat{\log u_{kjt}} = \log \frac{s_{kjt}}{s_{k0t}} - \hat{\beta}_k \log \frac{w_{kjt}}{w_{k0t}} - \widehat{\tilde{\sigma_{kg}}} \log s_{kjt|g}. \tag{11}$$

Then, to investigate which employer characteristics are correlated with labor supply, I estimate the following regression:

$$\widehat{\log u_{kjt}} = X'_{jt}\beta^u + \psi^u_n + \psi^u_p + e^u_{kjt}, \tag{12}$$

where $\widehat{\log u_{kjt}}$ are the estimated *average* preferences for amenities obtained from equation (11), X_{jt} represents observable employer characteristics (e.g., revenue, number of employees, total wage bill), β^u is a vector of coefficients, ψ^u_n are fixed effects for employer industry (with the two-digit NAICS code of the industry denoted by n), ψ^u_p are fixed effects for employer location (with the province denoted by p), and e^u_{jt} is an error term.

The estimated fixed effects are arbitrarily normalized, since one category is omitted (Newfoundland and Labrador for location, and Agriculture, Forestry, Fishing, and Hunting for industry). To compare the significance of the employer characteristics on the right-hand side of Equation (12) between immigrants and natives, I group them into three main categories: location fixed effects, industry fixed effects, and other employer characteristics. I then examine how much of the variation in *average* preferences is explained by each category. This is done through an "incremental R-squared" analysis, as follows. First, I estimate Equation (12) with all covariates included on the right-hand side, and record the R-squared of the full model, denoted as $R^2_{(1)}$. Next, I remove one group of covariates and re-estimate the equation. The new R-squared, after excluding that group of covariates, is denoted as $R^2_{(2)}$. The "incremental R-squared" for the excluded covariates is then calculated as $\Delta R^2 \equiv R^2_{(1)} - R^2_{(2)}$.

This measure captures the variation in $\widehat{\log(u_{kjt})}$ explained by the excluded covariates and can be used to evaluate their explanatory power.

Figure 7 shows that the location fixed effects explain a larger share of the variance in *average* preferences for immigrants compared to natives, consistent with the geographic clustering and higher BGCI documented in Section 5.3.1. Figure 7 also indicates that industry fixed effects, on average, explain a smaller share of the variance in *average* preferences for immigrants relative to natives, although the difference is much smaller compared to the difference for province fixed effects. These results are consistent with well-documented patterns of immigrants clustering in ethnic enclaves (e.g., Card 2001; Altonji and Card 1991) and having higher occupational mismatch (Aydede and Dar 2016).

To investigate how *average* preferences for amenities correlate with the risk of illness or injury on the job, I estimate Equation (12) separately for each k-group and then take the industry fixed effects and regress them on the average number of illnesses or injuries in each industry:

$$\hat{\psi^u_{kn}} = \eta_0 + \eta_1 x_n + \nu^u_{kn}, \tag{13}$$

where $\hat{\psi^u_{kn}}$ is the industry fixed effect for industry n obtained from estimating Equation (12), x_n is the rate of illnesses or injuries in industry n, and ν^u_{kn} is the error term.[13] The results, reported in Table A3 (Column (1)), suggest that industries with higher rates of illness or injury tend to have lower values of $\log u_{kjt}$. Thus, we see that workers tend to value working in safer industries. The literature suggests that immigrants often have more dangerous jobs compared to natives (Lay et al. 2018), and one may ask whether immigrants differ in their risk tolerance for injury or illness on the job relative to natives. However, the results presented in Table A3 (Column (2)) suggest that there is no significant difference in the value of working in a risky environment for immigrants compared to natives.

13. Data on illness or injury is obtained from the U.S. Bureau of Labor Statistics.

6 Counterfactual Analyses

6.1 Model-based Decomposition

In this section, I decompose the immigrant-native pay gap using counterfactual analyses. The procedure for each analysis is as follows. First, I select a subset of model parameters that will be manipulated in the counterfactual, such as the utility parameters that govern labor supply or the technology parameters that influence firm productivity. Next, I eliminate differences in the selected model parameters across immigrants and natives by setting them equal to a common value. Specifically, for counterfactuals involving utility parameters, I set them to a common value for all workers, and for counterfactuals involving firm productivity parameters, I set them to a common value for all firms. Then, I predict the effects on wages and employment by solving for the counterfactual equilibrium. To solve for the counterfactual equilibrium, I use an underrelaxed Jacobi iteration algorithm described in Appendix D. Importantly, this approach incorporates general equilibrium responses, including any adjustments in wage markdowns, marginal products of labor, or the distribution of workers across firms.[14] Finally, I summarize the results by reporting the counterfactual immigrant-native pay gap. This approach allows me to decompose the pay gap, isolating the contribution of the selected model parameters from the combined effect of all other factors.

Note that when $s_{kjt} = 0$, i.e., when we do not observe any workers of type k working for firm j at time t, the match-specific productivity parameter γ_{kjt} and the workers' deterministic preferences u_{kjt} cannot be separately identified. This is because we do not know whether firm j does not hire any workers of type k at time t because the match-specific productivity is very low ($\gamma_{kjt} \leq 0$) or because the firm amenities are very low ($u_{kjt} = -\infty$). Therefore, I do not conduct counterfactual exercises that manipulate the u_{kjt} or γ_{kjt} parameters, focusing

14. It is important to note that investigating a counterfactual scenario with "equal markdowns" across immigrants and natives would not be meaningful because markdowns arise endogenously in the model (see equation 8). Instead, we must alter the model primitives that generate markdowns and examine how these changes affect markdowns and overall earnings inequality.

instead on the other parameters. A promising avenue for future research is to find a way to impute one (or both) of these parameters for firm-worker type pairs with zero labor market share and then to incorporate match-specific and *average* preferences for amenities into the counterfactual analyses.

All of the counterfactuals in this paper are conducted after implementing combinations of the following restrictions:

A. The labor supply parameter β_k is set to the average value of β_k, i.e., $\beta_k^{CF} = \overline{\beta}$.

B. The labor supply parameter σ_{kg} is set to the average value of σ_{kg}, i.e., $\sigma_{kg}^{CF} = \overline{\sigma}$.

C. The firm productivity parameter $\tilde{\theta}_j$ (TFP) is set to the median value of $\tilde{\theta}_j$, i.e., $\tilde{\theta}_j^{CF} = \text{median}(\{\tilde{\theta}_1, \ldots, \tilde{\theta}_J\})$.

D. The firm productivity parameter α_j (returns to scale) is set to the median value of α_j, i.e., $\alpha_j^{CF} = \text{median}(\{\alpha_1, \ldots, \alpha_J\})$.

E. The unemployment benefits w_{0k} are set to the average value of w_{0k} in each year, i.e., $w_{0k}^{CF} = \overline{w}_0$.

F. The firm productivity parameters $\tilde{\theta}_j$ (TFP) and α_j (returns to scale) are set to the median values of these parameters within each city. Mathematically, for each city $\mathcal{C}$, the parameters are set to $\tilde{\theta}_j^{CF} = \text{median}(\{\tilde{\theta}_j \mid j \in \mathcal{C}\})$ and $\alpha_j^{CF} = \text{median}(\{\alpha_j \mid j \in \mathcal{C}\})$.

G. The firm productivity parameters $\tilde{\theta}_j$ (TFP) and α_j (returns to scale) are set to the median values of these parameters within each two-digit NAICS industry. Mathematically, for each industry $\mathcal{N}$, the parameters are set to $\tilde{\theta}_j^{CF} = \text{median}(\{\tilde{\theta}_j \mid j \in \mathcal{N}\})$ and $\alpha_j^{CF} = \text{median}(\{\alpha_j \mid j \in \mathcal{N}\})$.

H. The firm productivity parameters $\tilde{\theta}_j$ (TFP) and α_j (returns to scale) are set to the median values of these parameters within each unique combination of city and two-digit NAICS industry. Mathematically, for each industry $\mathcal{N}$ and city $\mathcal{C}$, the parameters are set to $\tilde{\theta}_j^{CF} = \text{median}(\{\tilde{\theta}_j \mid j \in \mathcal{N} \text{ and } j \in \mathcal{C}\})$ and $\alpha_j^{CF} = \text{median}(\{\alpha_j \mid j \in \mathcal{N} \text{ and } j \in \mathcal{C}\})$.

The counterfactuals listed above allow for a systematic decomposition of several underlying factors that contribute to the immigrant-native pay gap. I group them into the following categories:

1. Labor Supply (`A`, `B`, `E`): To quantify the impact of worker-side heterogeneity.
2. Firm Productivity (`C`, `D`, `F`, `G`, `H`): To quantify the importance of firm heterogeneity (`C`, `D`) and to isolate its importance within and between cities and industries (`F`, `G`, `H`).

My analytical strategy follows a "building-block" approach. First, I measure the direct contribution of each scenario in isolation. Next, I combine scenarios within the same category (e.g., `A+B`) to assess the full effect of a single channel. Finally, I construct comprehensive scenarios that bridge different categories (e.g., `A+B+C`) to investigate whether factors in different categories interact, either by amplifying or dampening one another.

Note that the counterfactual analyses reveal that heterogeneity in unemployment benefits is of limited importance for the immigrant-native pay gap (Counterfactual `E`).[15] Thus, I omit counterfactuals that build on `E` in the discussion below.

6.2 Counterfactual Results

6.2.1 Labor Supply Heterogeneity

The first set of counterfactuals demonstrates that a significant portion of the pay gap is driven by differences in labor supply curves. As shown in Panel A of Table 2, when I equalize the distributions of the idiosyncratic preference parameters across the two groups (Counterfactual `A+B`), the immigrant-native pay gap falls from 0.156 to 0.011. This represents a reduction of 14.5 percentage points, eliminating over 90% of the observed gap. This result

15. Results available upon request.

underscores the important role that heterogeneity in labor supply plays in generating earnings inequality between immigrants and natives. As described in Section 5, the estimated labor supply parameters imply that natives view firms as more substitutable, leading to a more elastic labor supply. This forces firms to offer them higher wages. Immigrants, in contrast, perceive fewer suitable job alternatives, resulting in a more inelastic labor supply and giving firms more labor market power over them.

Decomposing this effect reveals the influence of each preference parameter. Equalizing only the β_k parameter (Counterfactual `A`) reduces the gap by 4.9 percentage points to 0.107, while equalizing only the σ_{kg} parameter (Counterfactual `B`) reduces the gap by 8.1 percentage points to 0.075.

6.2.2 Firm Productivity and Worker Sorting

The second set of experiments explores the role of firm productivity. In Panel B of Table 2, setting all firms' TFP ($\tilde{\theta}_j$) and returns to scale (α_j) to the median (Counterfactual `C+D`) causes the pay gap to increase from 0.156 to 0.292. This 13.6 percentage point increase suggests that, on average, the existing distribution of firm productivity benefits immigrants more than natives.

The explanation for this lies in geographic sorting. While immigrants may work for more productive firms on average, they tend to work for less productive firms within each city. The evidence for this mechanism comes from Counterfactual `F`, where I equalize firm productivity *within* each city while maintaining differences in firm productivity *across* cities. In this scenario, the pay gap decreases from 0.156 to 0.014.

Eliminating firm productivity differences *within* industries (Counterfactual `G`) increases the pay gap to 0.295, an effect nearly as large as the full equalization scenario. This finding, however, should be interpreted with caution, as the σ_{kg} parameters do not vary across industries (see footnote 5). When I neutralize productivity differences at a more granular level within each city-industry cell (Counterfactual `H`), the pay gap is 0.153.

6.2.3 Interaction Effects

The final counterfactual analyses reveal that labor supply and firm productivity are not independent mechanisms. Panel C of Table 2 demonstrates these strong interaction effects. While equalizing β_k and σ_{kg} (Counterfactual `A+B`) reduces the baseline gap by 14.5 percentage points, its effect is much smaller in a world where all firms have the same TFP. To see this, consider a starting point where TFP is already equalized (Counterfactual `C`), yielding a high pay gap of 0.442. If I *then* equalize labor supply preferences (Counterfactual `A+B+C`), the gap falls to 0.401. The marginal impact of the preference change is now only a 4.1 percentage point reduction (0.442 − 0.401), compared to the 14.5 percentage point reduction in the baseline scenario. This shows that the wage penalty associated with immigrants' inelastic labor supply is magnified by heterogeneity in TFP across firms.

The heterogeneity of other parameters in the counterfactual can determine the sign of a model parameter's contribution, sometimes causing it to reverse completely. While equalizing β_k alone (counterfactual `A`) reduces the gap by 4.9 percentage points, its effect reverses in counterfactuals where there are also no differences in TFP across firms. For instance, when TFP is homogeneous (Counterfactual `C`, gap of 0.442), adding the equalization of β_k (Counterfactual `A+C`) *increases* the pay gap to 0.522. A similar reversal occurs when only returns to scale are equalized (comparing Counterfactuals `D` and `A+D`).

7 Conclusion

In this paper, I investigate the determinants of the immigrant-native pay gap, focusing on the roles of labor market power and firm productivity. The results indicate that immigrants are exposed to greater labor market power relative to natives, with firms marking down immigrant wages by 23% and native wages by 16% on average. Conversely, immigrants tend to work at more productive firms—a striking finding that underscores the importance of the structural approach in disentangling these opposing mechanisms.

I explore the sources of immigrants' increased exposure to labor market power and find that both greater horizontal differentiation and higher labor market concentration contribute. These results suggest that the immigrant wage penalty arises largely because immigrants perceive fewer suitable job alternatives relative to natives. While this framework quantifies the extent of horizontal differentiation, identifying the specific amenities or frictions generating it remains a promising avenue for future research.

Finally, I conduct a novel decomposition of the pay gap using counterfactual analyses that account for general equilibrium responses. These analyses reveal that while labor market power and labor supply heterogeneity widen the pay gap, firm productivity heterogeneity narrows it. Furthermore, the counterfactuals highlight important interdependencies between these factors; specifically, the wage penalty resulting from labor supply heterogeneity is significantly influenced by the underlying distribution of firm productivity.

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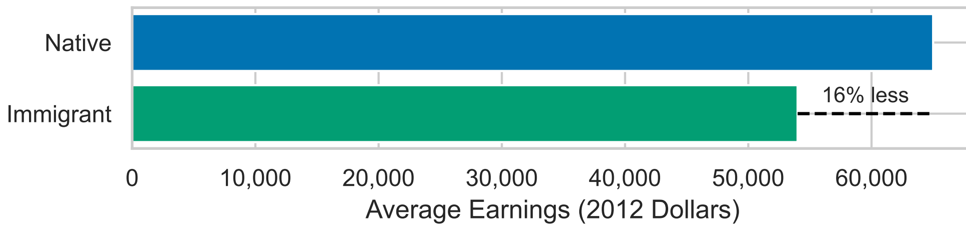
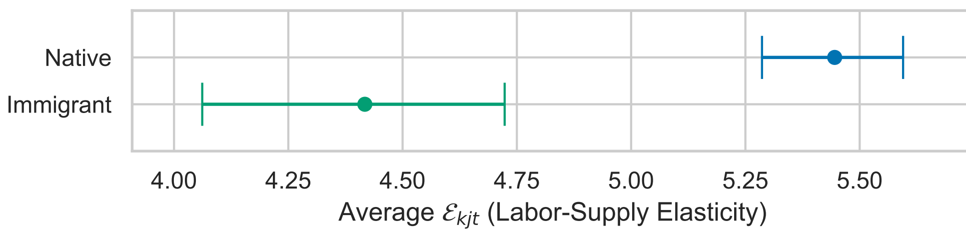
Main Figures

Figure 1: Earnings, Labor Supply Elasticities, and Wage Markdowns by Immigrant Status

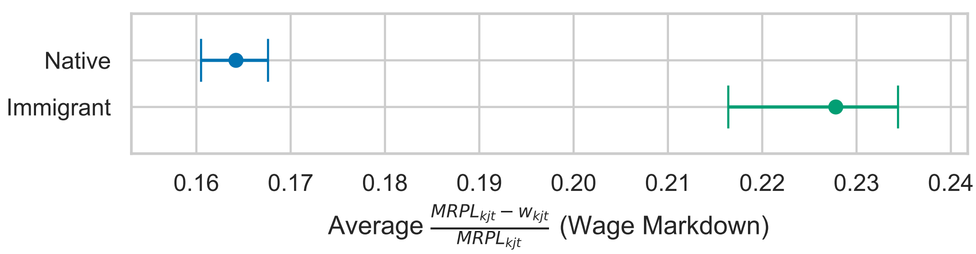
(a) Earnings Gap



(b) Labor Supply Elasticities



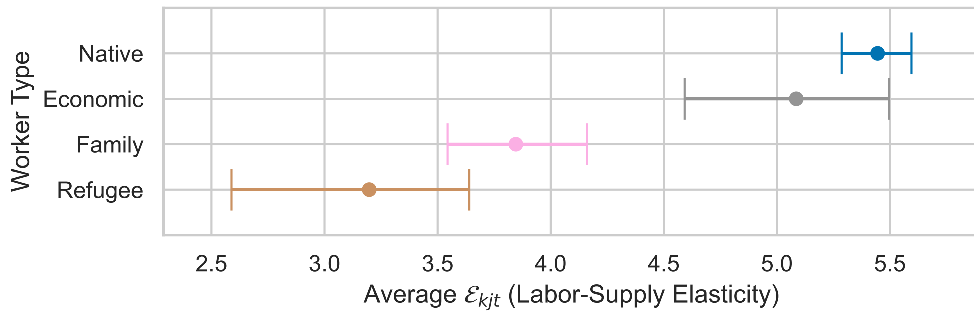
(c) Wage Markdowns



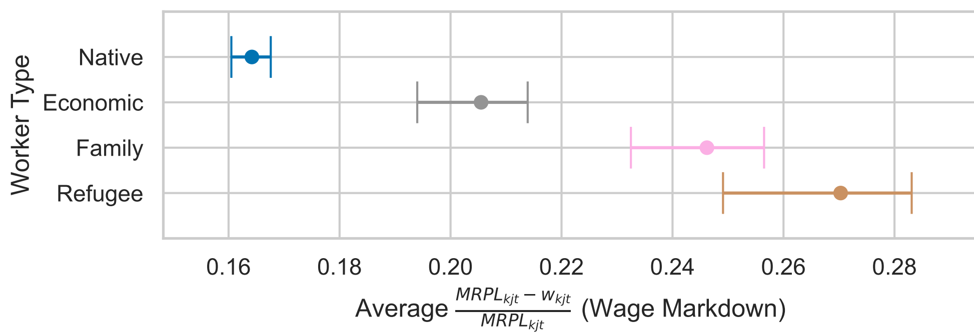
Notes: This figure presents the pay gap between immigrants and natives, alongside differences in their estimated firm-specific labor supply elasticities and wage markdowns. Panel (a) illustrates earnings differentials by immigrant status. Panels (b) and (c) present the main estimates of employment-weighted firm-specific labor supply elasticities and wage markdowns, respectively. Wage markdowns are defined as the absolute percentage below the MRPL, i.e., $(\text{MRPL}_{kjt} - w_{kjt})/\text{MRPL}_{kjt}$. Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD. Data on earnings used to construct Panel (a) come from the T4 database.

Figure 2: Labor Supply Elasticities and Wage Markdowns by Admission Category

(a) Labor Supply Elasticities



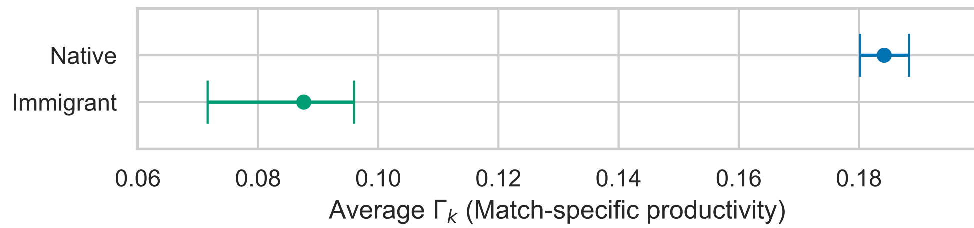
(b) Wage Markdowns



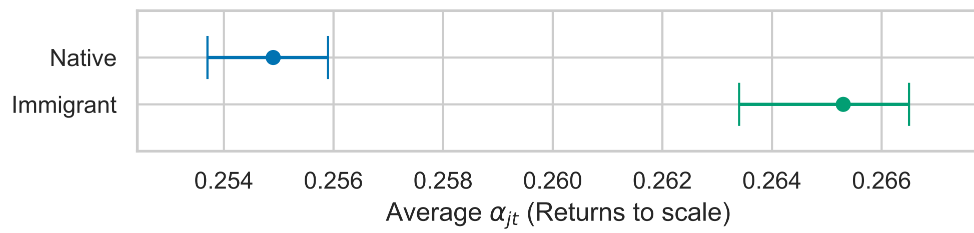
Notes: This figure presents the main estimates of employment-weighted firm-specific labor supply elasticities and wage markdowns for native-born workers and immigrants by admission category (economic class, family class, and refugees). Panel (a) reports the firm-specific labor supply elasticities, and Panel (b) reports the wage markdowns. Wage markdowns are defined as the absolute percentage below the MRPL, i.e., $(\text{MRPL}_{kjt} - w_{kjt})/\text{MRPL}_{kjt}$. Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure 3: Firm Productivity Parameters by Immigrant Status

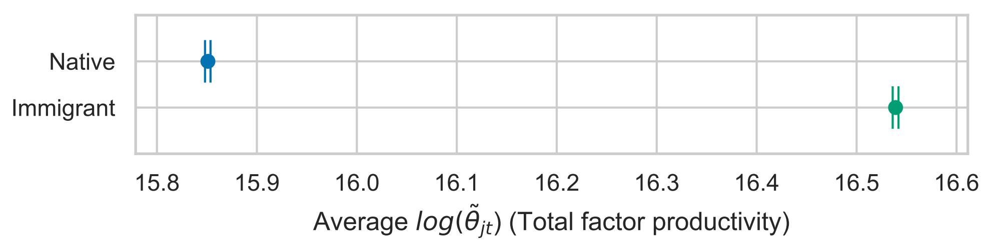
(a) Match-Specific Productivity



(b) Returns to Scale



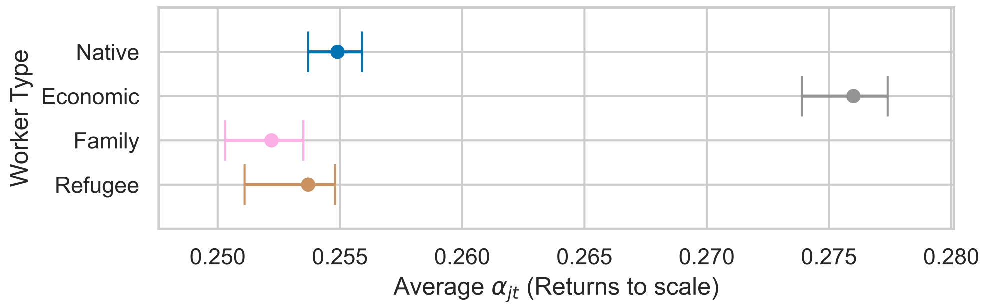
(c) Total Factor Productivity



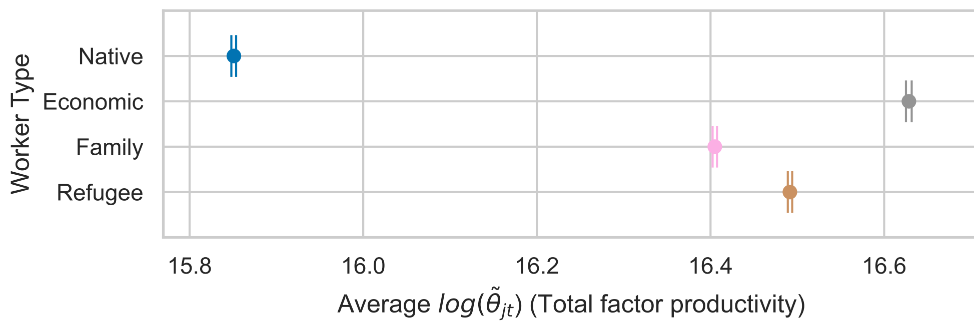
Notes: This figure presents the main estimates of the labor demand parameters for natives and immigrants. Panel (a) shows the match-specific productivity parameters (γ_{kjt}), which are normalized within each firm; to compare across individuals employed by different firms, I first estimate Equation (10) (with female natives as the omitted category) and then calculate employment-weighted averages of the worker-type fixed effects from the regression. Panel (b) displays employment-weighted averages of employer returns to scale (α_{jt}), and Panel (c) displays employment-weighted averages of employer total factor productivity ($\tilde{\theta}_{jt}$). The values in Panels (b) and (c) represent the average firm characteristics faced by workers in each group; conceptually, they are calculated by assigning each worker their employer's parameter value and averaging across all workers in the respective group. Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure 4: Firm Productivity by Admission Category

(a) Returns to Scale

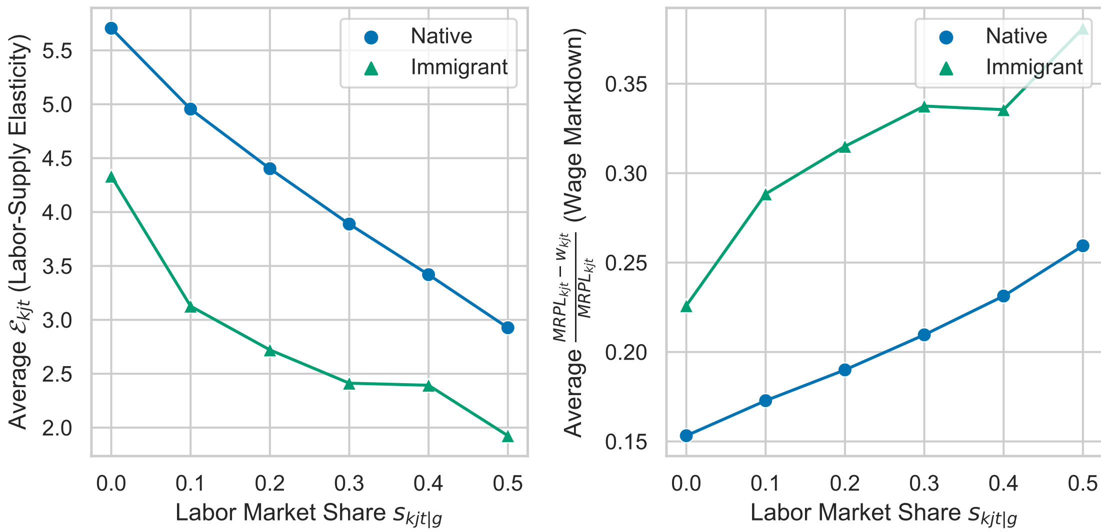


(b) Total Factor Productivity



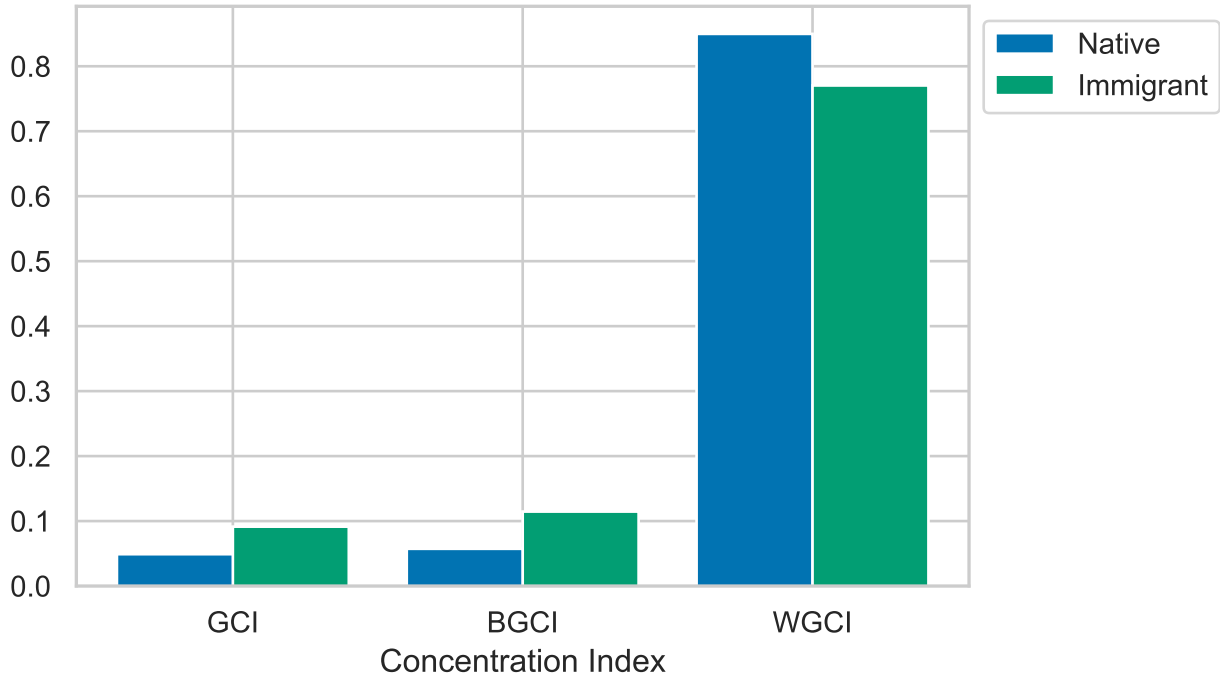
Notes: This figure presents the main estimates of the firm productivity parameters for natives and the three admission categories of permanent residency: the Economic Class, the Family Class, and the Humanitarian and Refugee Class. These values represent the average firm characteristics faced by workers in each group; conceptually, they are calculated by assigning each worker their employer's parameter value and averaging across all workers in the respective group. Panel (a) displays the employment-weighted average returns to scale (α_{jt}), and Panel (b) presents the employment-weighted averages of TFP ($\tilde{\theta}_{jt}$). Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure 5: Labor Supply Elasticity and Markdowns by Labor Market Share



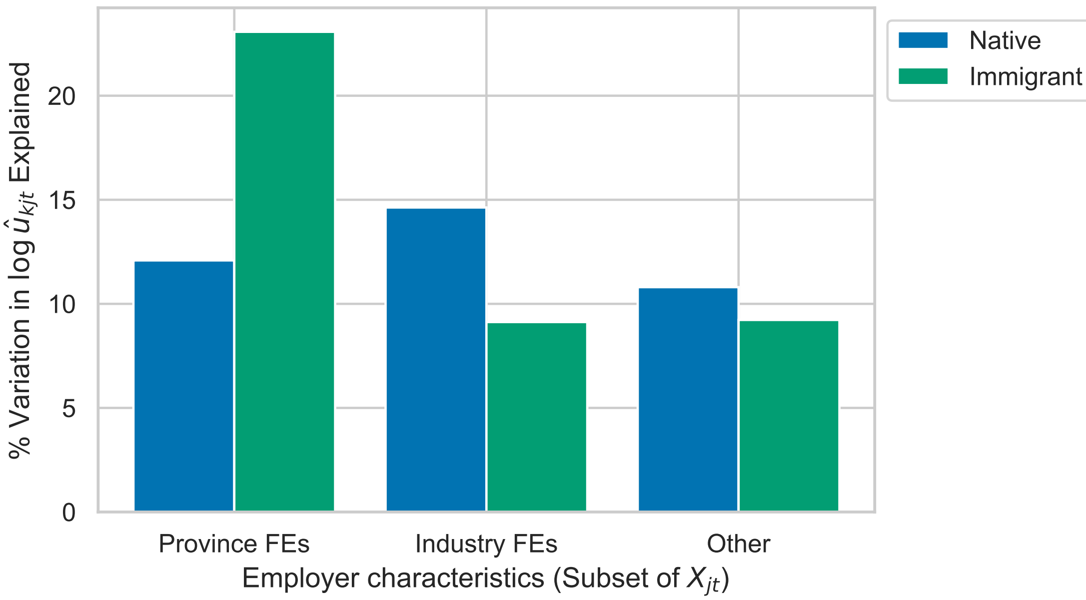
Notes: This figure illustrates the relationship between the firm-specific labor supply elasticity, wage markdown, and employer labor market share, separately for immigrants and natives. Labor market share, $s_{kjt|g}$, is defined as the share of type-k workers in market g employed by firm j at time t: $s_{kjt|g} \equiv l_{kjt}/\left(\sum_{j\in\mathcal{J}_g} l_{kjt}\right)$, where $\mathcal{J}_g$ is the set of firms in market g. Wage markdowns are defined as the absolute percentage below the MRPL, i.e., $(\text{MRPL}_{kjt} - w_{kjt})/\text{MRPL}_{kjt}$. *Source:* Author's calculations using the CEEDD.

Figure 6: Measures of Labor Market Concentration by Immigrant Status



Notes: This figure presents the main estimates of the Generalized Concentration Index (GCI), Within-group Generalized Concentration Index (WGCI), and Between-group Generalized Concentration Index (BGCI) (see Section 5.3.1), separately for immigrants and natives. *Source:* Author's calculations using the CEEDD.

Figure 7: Variation in Estimated Average Preferences for Amenities Explained by Observable Employer Characteristics



Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with *average* preferences for amenities, separately for immigrants and natives. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate Equation 12 with all covariates included on the right-hand side and record the R-squared of the full model, denoted as R^2_{full}. Next, I remove one group of covariates (province fixed effects, industry fixed effects, or other characteristics) and re-estimate the equation. The new R-squared, after excluding this group of covariates, is denoted as $R^2_{partial}$. The incremental R-squared is then calculated as $\Delta R^2 \equiv R^2_{full} - R^2_{partial}$.

Main Tables

Table 1: Summary Statistics

		Ever Permanent Residents			
	Natives	All	Economic	Family	Refugee
	(1)	(2)	(3)	(4)	(5)
Share male	65.0	61.5	62.3	56.3	68.8
Mean age	42.1	41.7	41.7	41.1	42.6
Mean earnings (All firms)	65,000	54,000	60,000	48,000	47,000
Mean earnings ("B" firms only)	55,000	42,000	45,000	39,000	38,000
Mean earnings ("S" firms only)	72,000	56,000	62,000	49,000	48,000
Share in Quebec	27.1	13.6	14.6	11.3	14.5
Share in Ontario	35.9	54.5	51.7	57.3	59.1
Share in British Columbia	11.2	15.1	15.8	16.5	9.4
Share at "B" firms	59.3	90.0	90.0	89.6	90.8
Mean share immigrants at firm	11.6	51.0	49.9	53.0	51.1
Median number of workers	29	75	85	63	72
Mean log revenue	16.5	17.2	17.4	17.1	17.0
Median log revenue	16.2	17.0	17.2	16.8	16.9
Mean log revenue per worker	12.8	12.8	12.8	12.7	12.7
Median log revenue per worker	12.8	12.7	12.8	12.7	12.7
Number of person-year's	74,530,000	17,610,000	9,520,000	5,400,000	2,680,000
Number of persons	10,300,000	2,950,000	1,660,000	860,000	430,000
Number of Enterprise ID's	900,000	450,000	320,000	260,000	150,000
Number of firms	2,600,000	735,000	509,000	372,000	209,000

Notes: This table contains summary statistics for the sample described in Section 4. Column (1) contains native-born workers, Column (2) contains all individuals who are or have been permanent residents, and columns (3), (4), and (5) split the individuals in Column (2) based on the immigrant admission category. Firm-level statistics are calculated as averages across the employees belonging to each respective column group (e.g., averages across all immigrant employees for Column (2)). "B" firms are those that hire *both* immigrants and natives, while "S" firms are those that are *segregated*, i.e., they hire *only* immigrants or *only* natives. All monetary units are in $2012 dollars. Numbers in the table are rounded to comply with Statistics Canada's vetting rules for intermediate output (unrounded values will be provided for publication). *Source:* Author's calculations using the CEEDD. Revenue comes from the NALMF, earnings data comes from the T4 database, immigration status and admission category come from the IMDB, and other demographic variables (including location) come from the T1PMF.

Table 2: Counterfactual Analyses

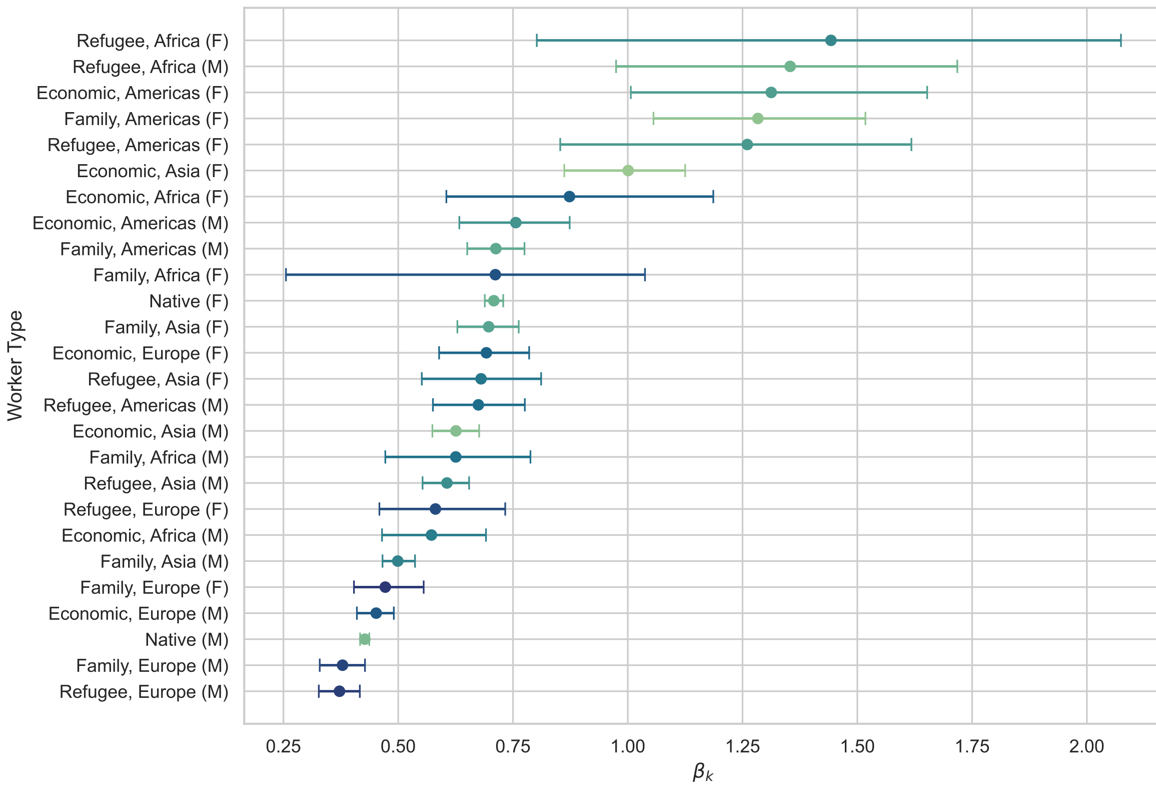
Counterfactual	Description	Pay Gap
Panel A: Labor Supply Counterfactuals		
A	Avg. β_k	0.107
B	Avg. σ_{kg}	0.075
A+B	Avg. β_k, σ_{kg}	0.011
Panel B: Firm Productivity Counterfactuals		
C	Median $\tilde{\theta}_j$	0.442
D	Median α_j	0.217
C+D	Median $\tilde{\theta}_j, \alpha_j$	0.292
F	CMA median $\tilde{\theta}_j, \alpha_j$	0.014
G	Industry median $\tilde{\theta}_j, \alpha_j$	0.295
H	Industry-CMA median $\tilde{\theta}_j, \alpha_j$	0.153
Panel C: Labor Supply and Firm-Productivity Interactions		
A+C	Avg. β_k, med. $\tilde{\theta}_j$	0.522
A+D	Avg. β_k, med. α_j	0.253
A+B+C	Avg. β_k, σ_{kg}, med. $\tilde{\theta}_j$	0.401
A+B+D	Avg. β_k, σ_{kg}, med. α_j	0.089
A+C+D	Avg. β_k, med. $\tilde{\theta}_j, \alpha_j$	0.193
B+C+D	Avg. σ_{kg}, med. $\tilde{\theta}_j, \alpha_j$	0.231

Notes: This table shows the results from the counterfactual analyses used to decompose the immigrant-native pay gap (see Section 6). The first column uses the key described in Section 6 to describe the counterfactual analysis presented in each row of the table. The second column provides a short description of the counterfactual analysis by stating which variables have been manipulated (set to either the mean or median value in the data). The third column reports the counterfactual pay gap, defined as $(\overline{w}_{k\in\text{nat}} - \overline{w}_{k\in\text{imm}})/\overline{w}_{k\in\text{nat}}$. Panel A presents results for the counterfactuals demonstrating the importance of differences in labor supply. Panel B presents results for counterfactuals demonstrating the importance of firm productivity. Panel C presents counterfactuals demonstrating the existence of interaction effects between firm productivity and labor supply. *Source:* Author's calculations using the CEEDD.

Online Appendix

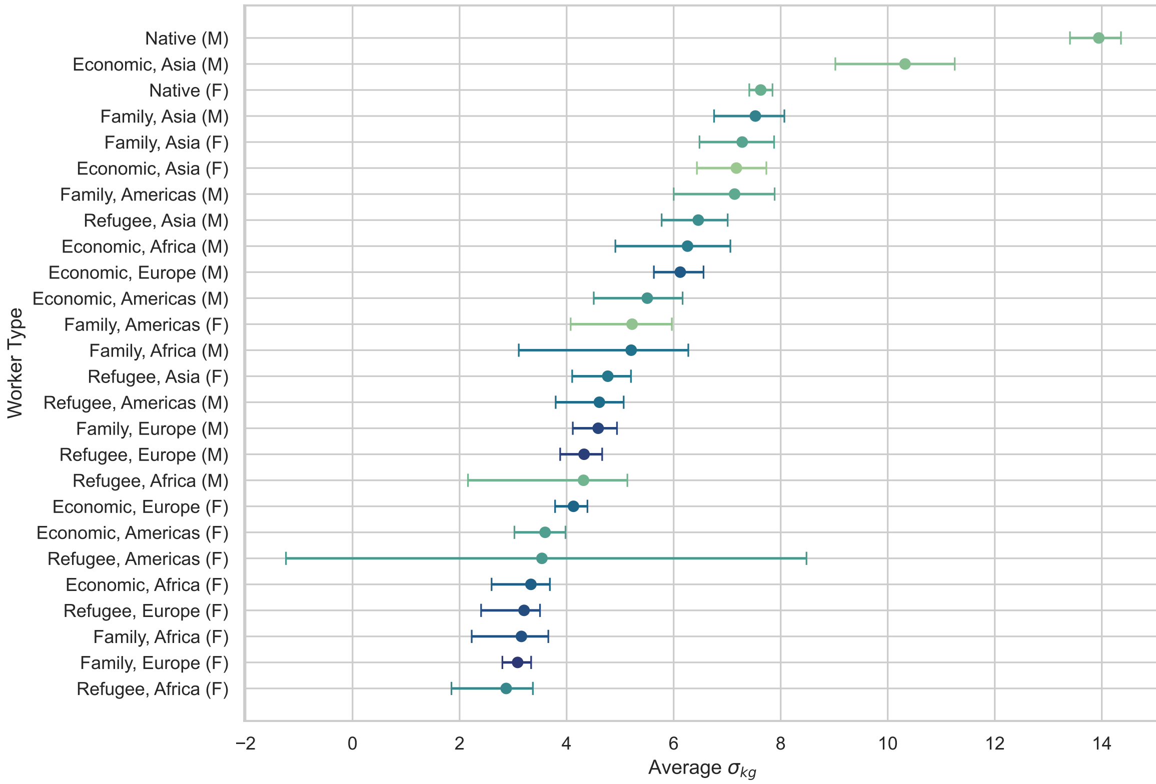
A Appendix Figures and Tables

Figure A1: Estimates of β_k by k-group



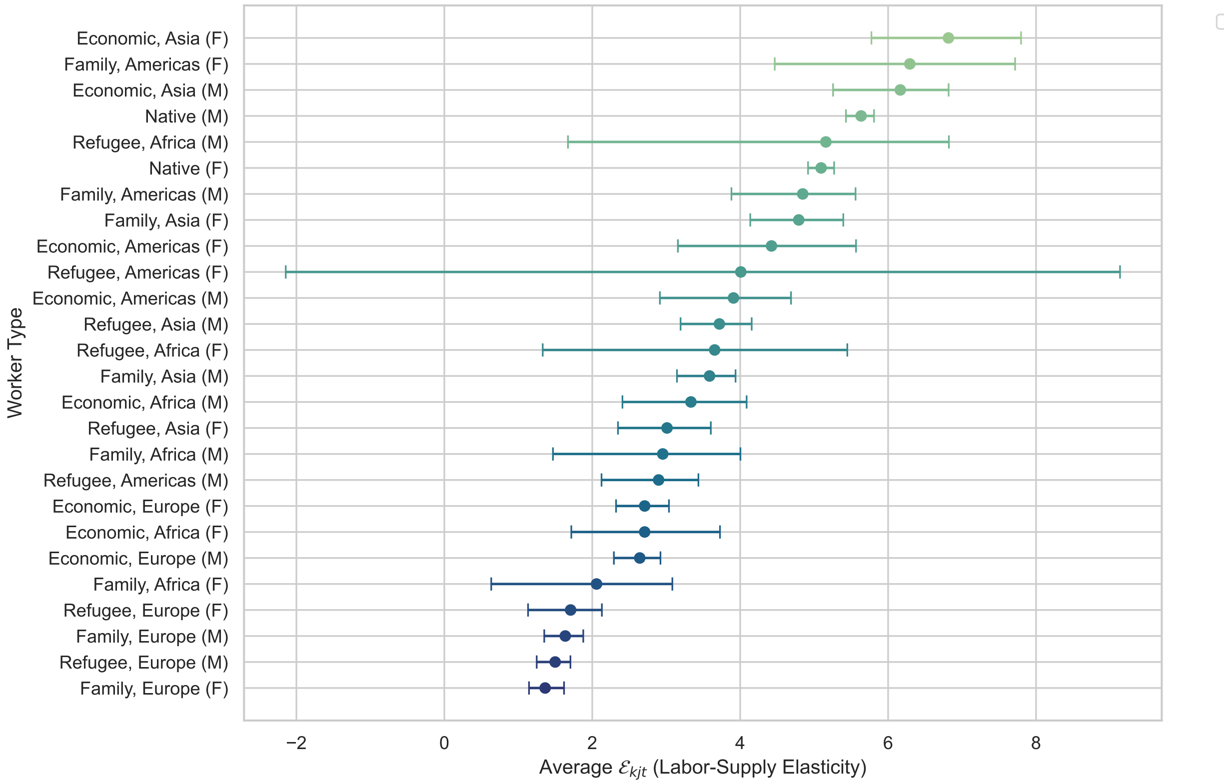
Notes: This figure shows the estimates of β_k, which represents the marginal utility of the wage in the utility function (see equation 1). IV estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure A2: Estimates of σ_{kg} by k-group



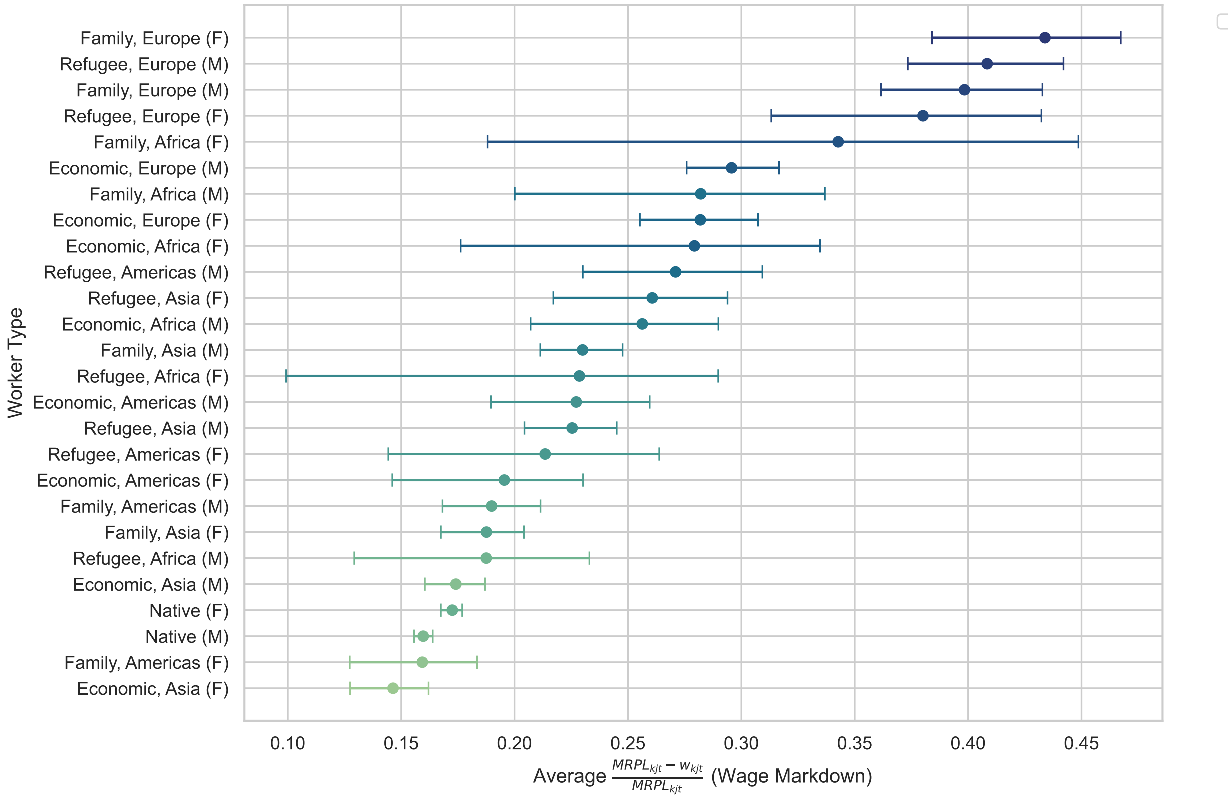
Notes: This figure shows the estimates of the average σ_{kg} for each k-group. The parameter σ_{kg} is the "nest parameter" related to the correlation of idiosyncratic preferences (see section 3.2). "Average" refers to the employment-weighted average in the data. IV estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure A3: Heterogeneity in labor supply Elasticities by k-Group



Notes: This figure presents the main estimates of labor supply elasticities for each k-group. "Average" refers to the employment-weighted average in the data. IV estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

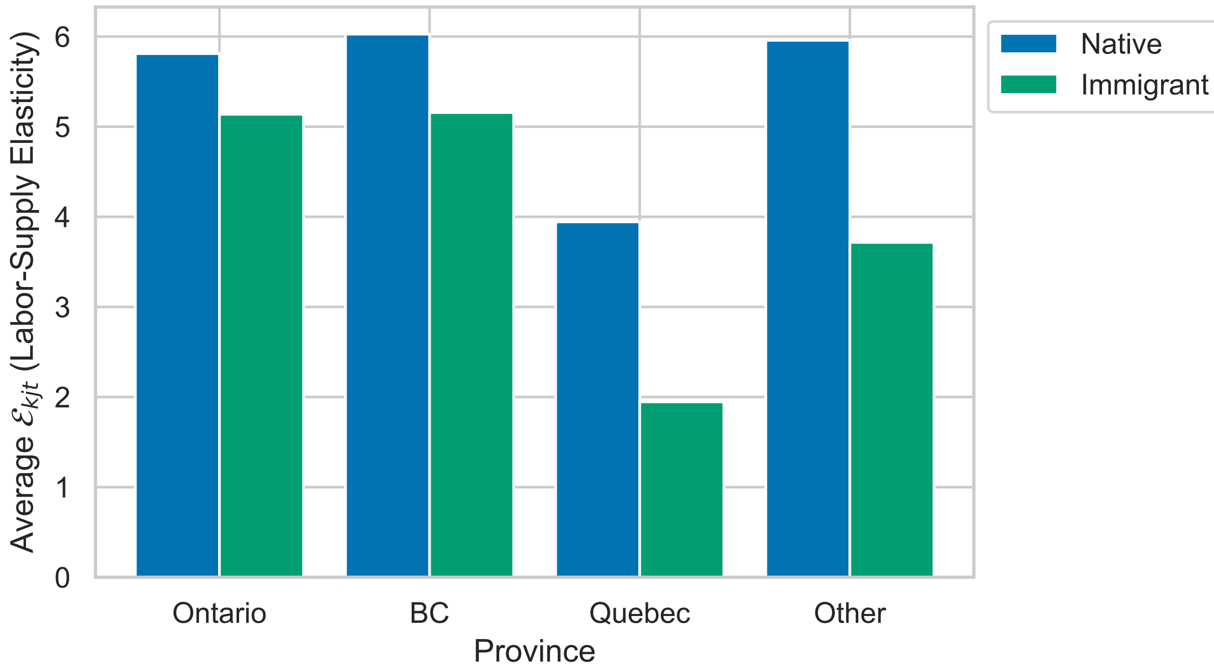
Figure A4: Heterogeneity in Wage Markdowns by k-Group



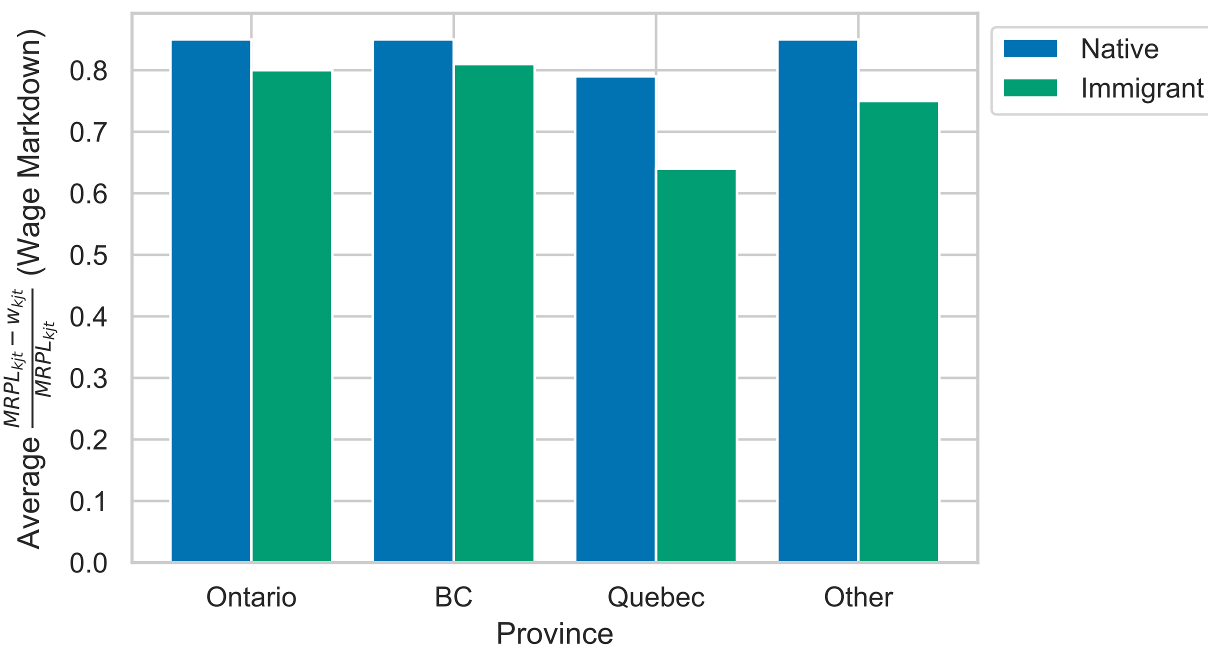
Notes: This figure presents the main estimates of wage markdowns for each k-group. Wage markdowns are defined as the absolute percentage below the MRPL, i.e., $(MRPL_{kjt} - w_{kjt})/MRPL_{kjt}$. "Average" refers to the employment-weighted average in the data. IV estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure A5: Heterogeneity in labor supply Elasticities and Wage Markdowns by Province

(a) labor supply Elasticities

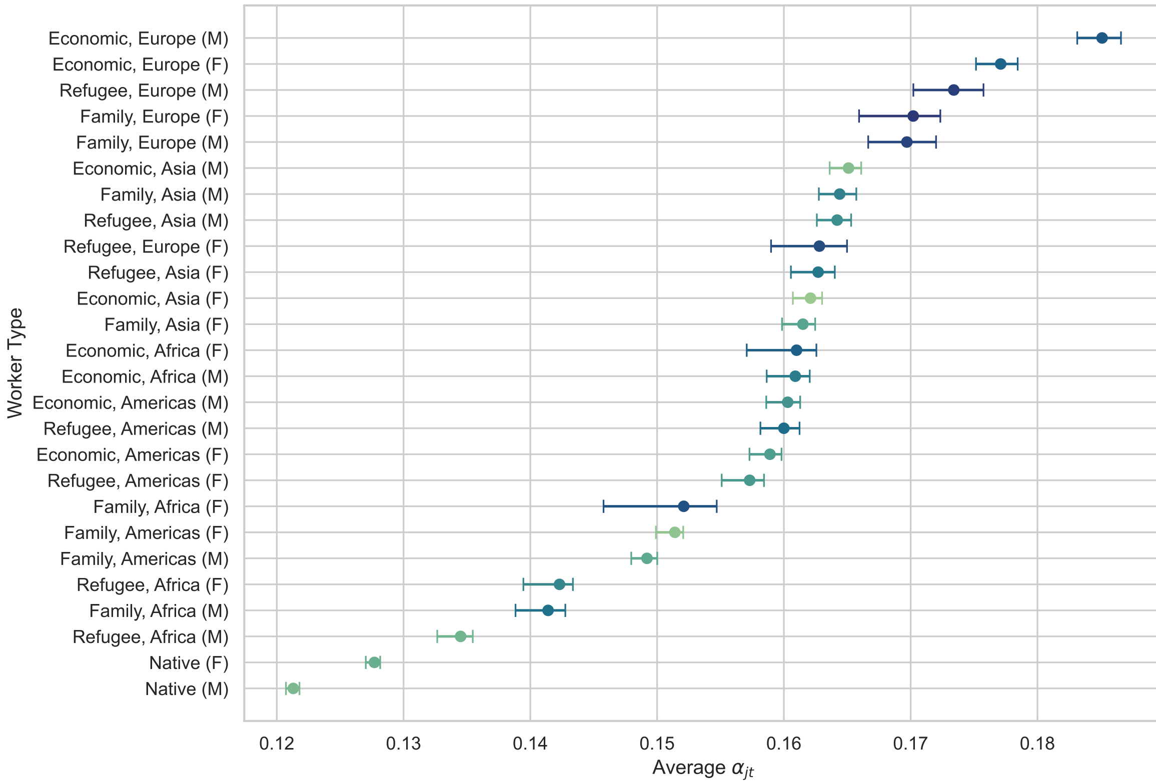


(b) Wage Markdowns



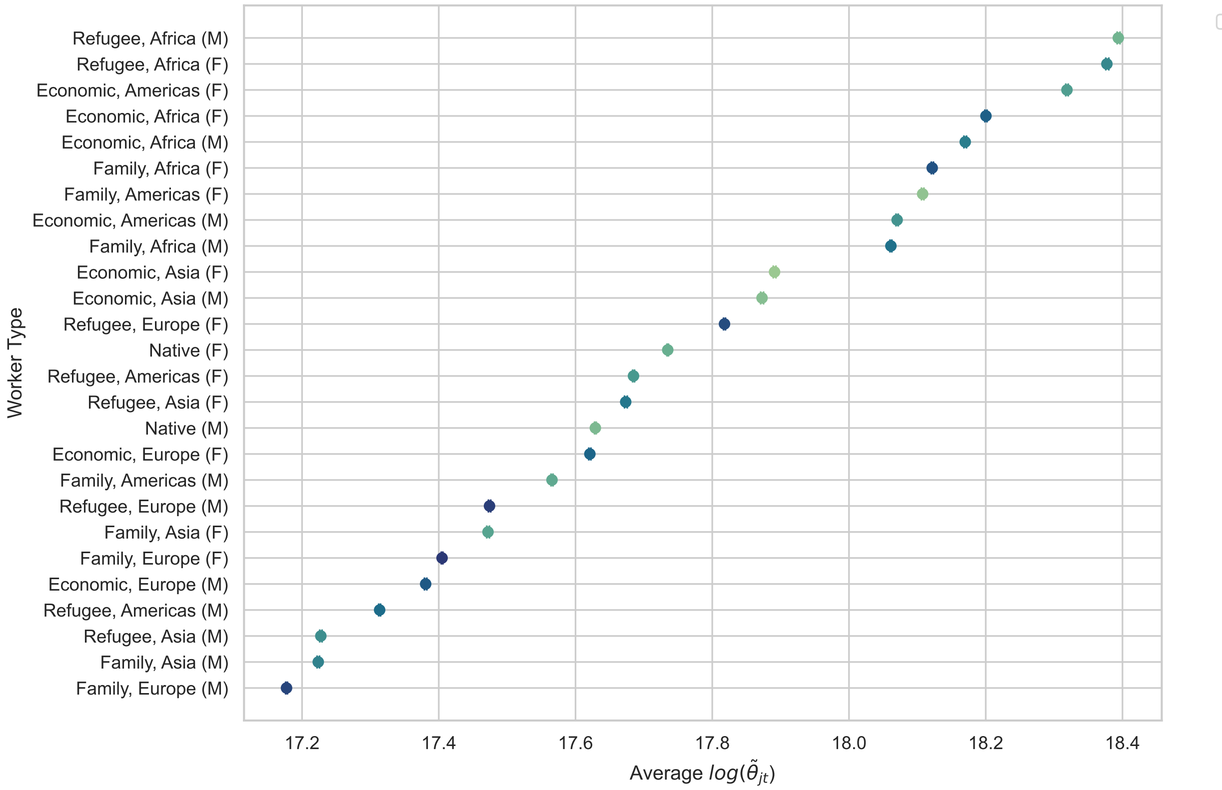
Notes: This figure presents the main estimates of labor supply elasticities (Panel a) and wage markdowns (Panel b) across provinces. Wage markdowns are defined as the absolute percentage below the MRPL. "Average" refers to the employment-weighted average in the data. *Source:* Author's calculations using the CEEDD.

Figure A6: Estimates of average returns to scale by k-group



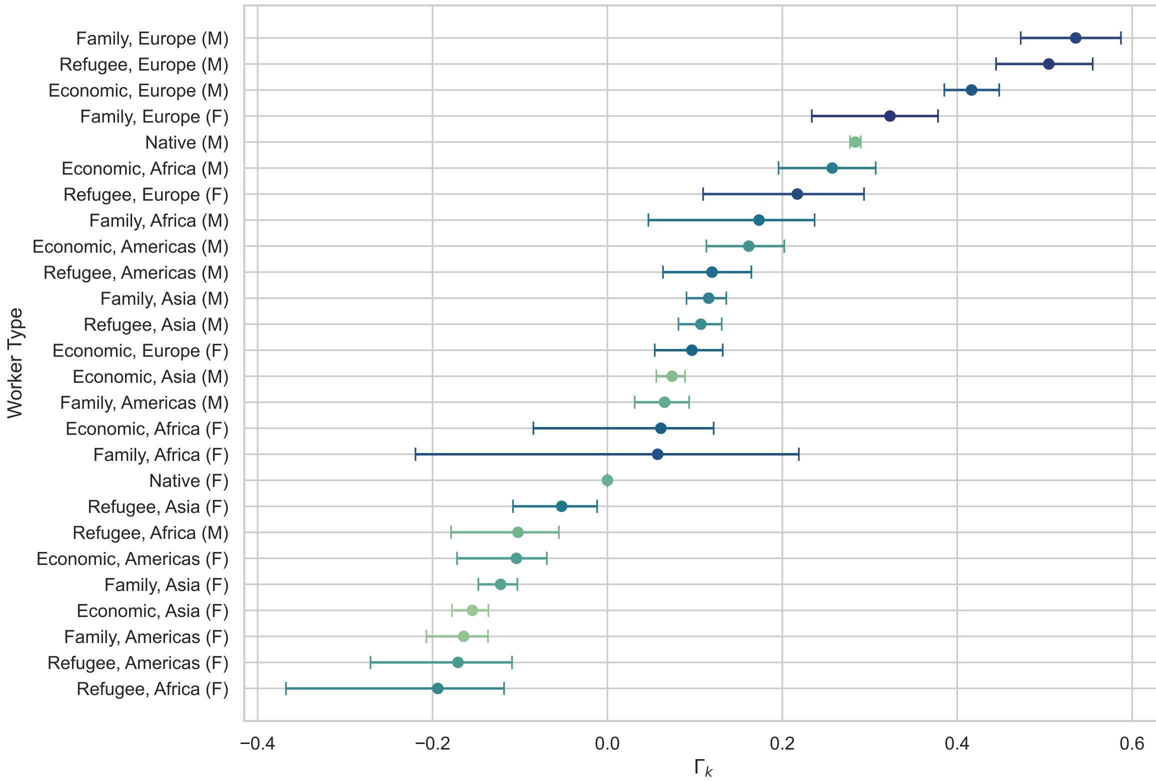
Notes: This figure shows the estimates of the average α_{jt} for each k-group. The parameter α_{jt} captures the returns to scale in the production function (see equation 7). "Average" refers to the employment-weighted average in the data. IV estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure A7: Estimates of average TFP by k-group



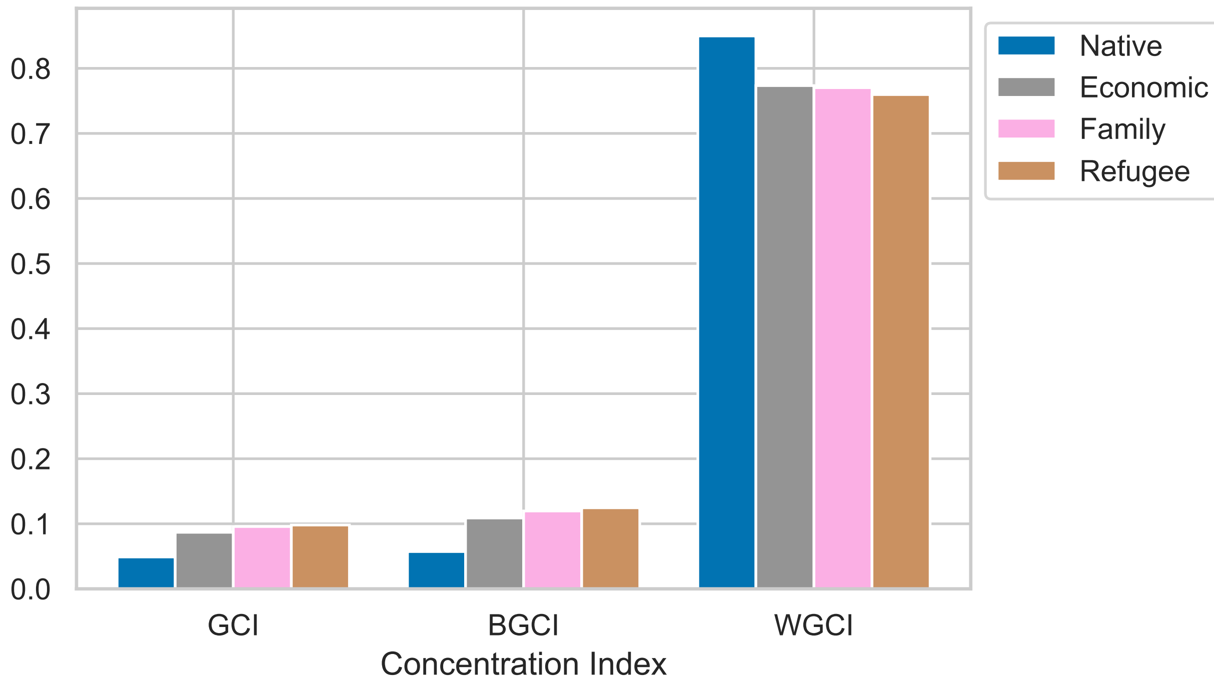
Notes: This figure shows the estimates of the average $\log(\tilde{\theta}_{jt})$ for each k-group. The parameter $\log(\tilde{\theta}_{jt})$ captures total factor productivity (TFP) in the production function (see equation 7). "Average" refers to the employment-weighted average in the data. IV estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure A8: Heterogeneity in Match-Specific Productivity by k-Group



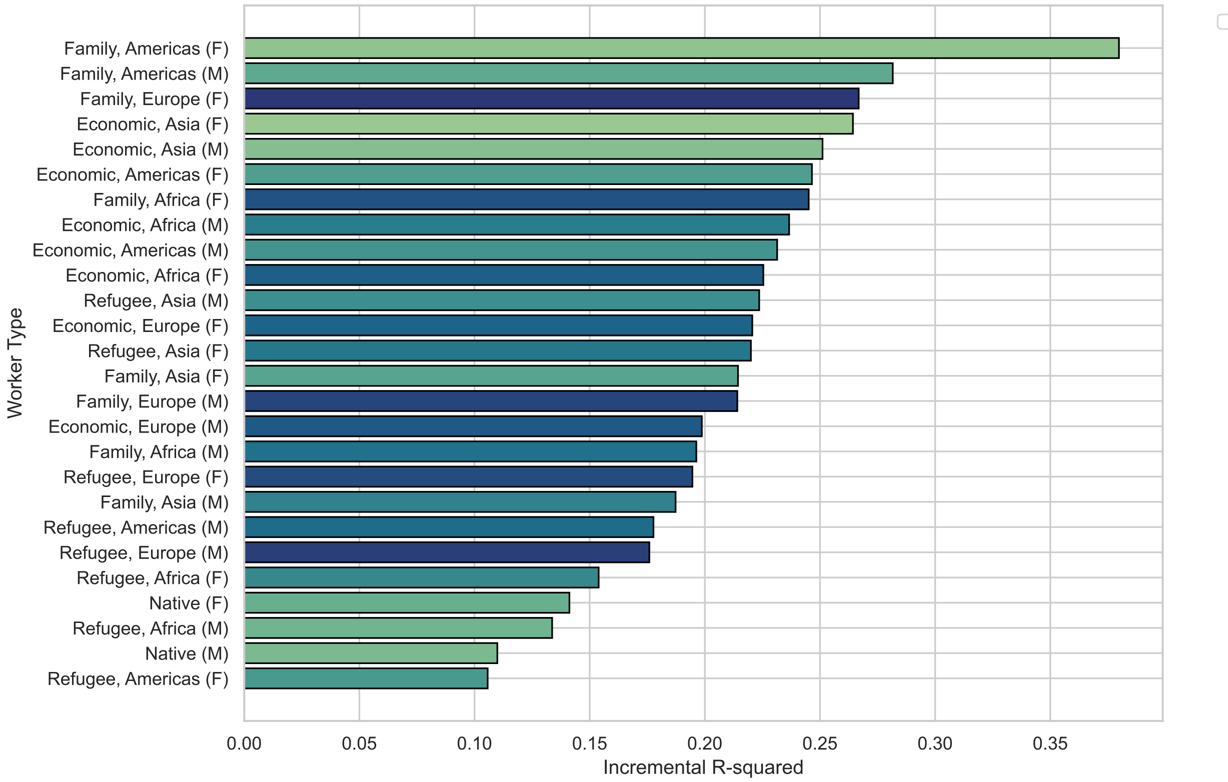
Notes: This figure presents the main estimates of worker skill (Γ_k) for each k-group, obtained from the estimation of equation 10. Ordinary Least Squares (OLS) estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the CEEDD.

Figure A9: Concentration Indices



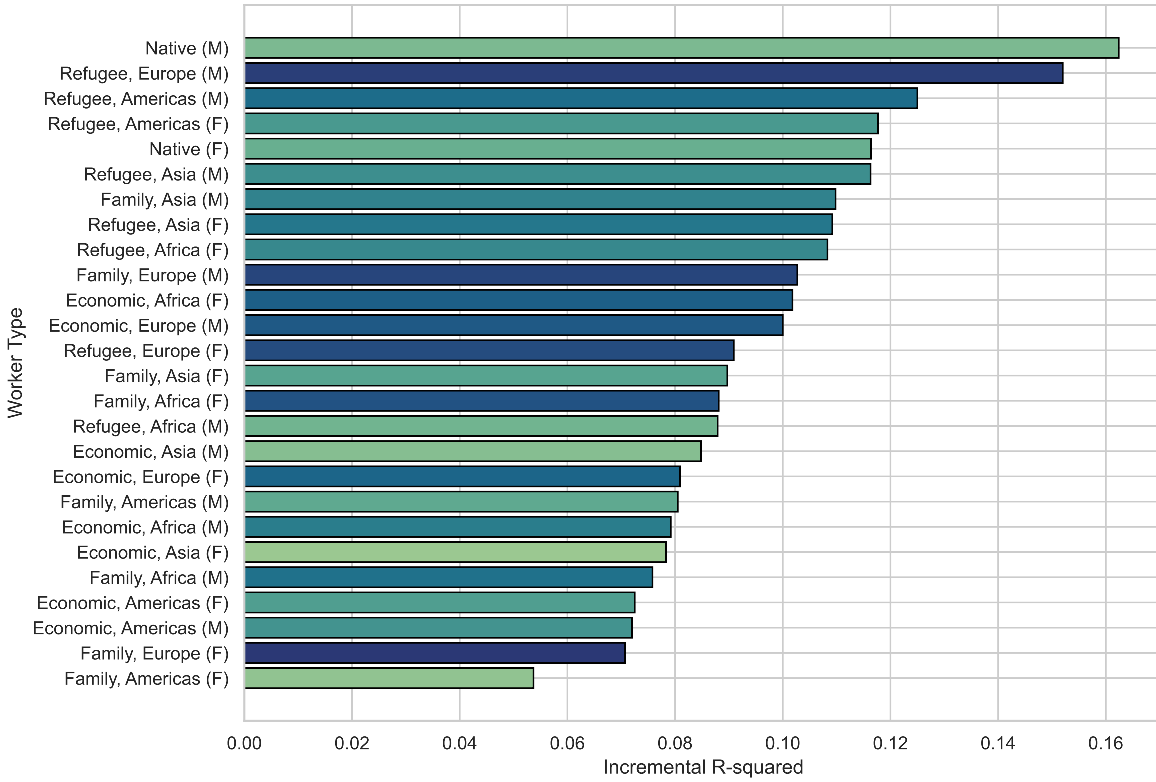
Notes: This figure presents the main estimates of the Generalized Concentration Index (GCI), Within-group Generalized Concentration Index (WGCI), and Between-group Generalized Concentration Index (BGCI) (see Section 5.3.1). The top panel shows these average values for immigrants and non-immigrants. The bottom panel shows average values for non-immigrants and three immigrant sub-groups: economic class, family class, and refugees. "Average" refers to the employment-weighted average in the data. *Source:* Author's calculations using the CEEDD.

Figure A10: Incremental R-squared Analyses (Provinces)



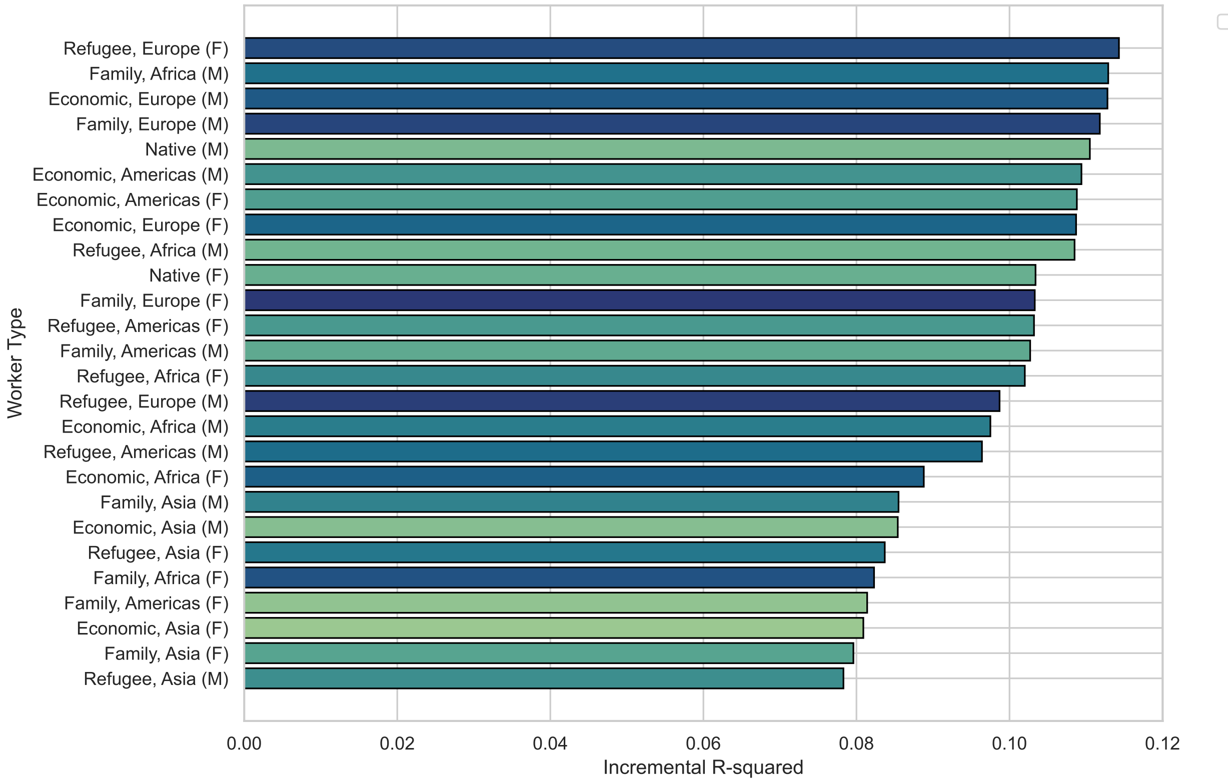
Notes: This figure presents results from incremental R-squared analyses investigating factors correlated with deterministic preferences for amenities. The incremental R-squared is calculated as $\Delta R^2_{prov} \equiv R^2_{full} - R^2_{-prov}$, where R^2_{full} is the R-squared from the full model and R^2_{-prov} is the R-squared after excluding province fixed effects. *Source:* Author's calculations using the CEEDD.

Figure A11: Incremental R-squared Analyses (Industries)



Notes: This figure presents results from incremental R-squared analyses investigating factors correlated with deterministic preferences for amenities. The incremental R-squared is calculated as $\Delta R^2_{ind} \equiv R^2_{full} - R^2_{-ind}$, where R^2_{full} is the R-squared from the full model and R^2_{-ind} is the R-squared after excluding industry fixed effects. *Source:* Author's calculations using the CEEDD.

Figure A12: Incremental R-squared Analysis (other employer characteristics)



Notes: This figure presents results from incremental R-squared analyses investigating factors correlated with deterministic preferences for amenities. The incremental R-squared is calculated as $\Delta R^2_{tv} \equiv R^2_{full} - R^2_{-tv}$, where R^2_{full} is the R-squared from the full model and R^2_{-tv} is the R-squared after excluding time-varying firm characteristics. *Source:* Author's calculations using the CEEDD.

Table A1: F-statistics from the first stage of estimating equation 5

$k-$ group	β_k	$\sigma_{k,BC}$	$\sigma_{k,ON}$	$\sigma_{k,QC}$	$\sigma_{k,Other}$
Non-immigrant (F)	1171	12040	13351	10776	12730
Non-immigrant (M)	1972	15087	16365	13571	17089
Economic, Americas (F)	12	330	309	412	374
Economic, Europe (F)	54	942	950	851	819
Economic, Africa (F)	10	261	209	214	163
Economic, Asia (F)	69	1869	1845	1451	1432
Economic, Americas (M)	38	598	468	703	712
Economic, Europe (M)	131	1420	1547	1526	1659
Economic, Africa (M)	32	526	462	480	567
Economic, Asia (M)	144	2873	2826	2553	2557
Family, Americas (F)	22	360	372	245	336
Family, Europe (F)	57	335	442	501	332
Family, Africa (F)	5	94	89	57	97
Family, Asia (F)	115	1068	1099	915	924
Family, Americas (M)	88	574	616	605	767
Family, Europe (M)	75	711	717	732	820
Family, Africa (M)	15	142	152	141	186
Family, Asia (M)	191	1385	1630	1300	1915
Refugee, Americas (F)	9	111	141	116	116
Refugee, Europe (F)	25	271	268	200	248
Refugee, Africa (F)	4	113	60	55	91
Refugee, Asia (F)	41	382	363	359	361
Refugee, Americas (M)	38	268	315	189	390
Refugee, Europe (M)	76	451	531	461	583
Refugee, Africa (M)	10	234	181	254	181
Refugee, Asia (M)	125	809	908	826	877

This table presents partial F-statistics from the first-stage of the estimation of equation 14. Note that when estimating the model, the σ_{kg} parameter is assumed to be constant within each unique combination of worker type and province group (Ontario, Quebec, British Columbia, all other provinces). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table A2: Overview of labor supply Parameter Estimates

Panel A: Estimated Values in the Full Sample					
		IV	95% CI	OLS	95% CI
Marginal utility wages	β_k	0.56	[0.53; 0.56]	0.24	[0.24; 0.24]
Nest parameter	σ_{kg}	10.79	[10.77; 11.43]	1.21	[1.2; 1.21]
Panel B: Estimated Values for Natives Only					
		IV	95% CI	OLS	95% CI
Marginal utility wages	β_k	0.53	[0.5; 0.53]	0.28	[0.28; 0.28]
Nest parameter	σ_{kg}	11.73	[11.68; 12.4]	1.23	[1.23; 1.23]
Panel C: Estimated Values for Immigrants Only					
		IV	95% CI	OLS	95% CI
Marginal utility of wages	β_k	0.7	[0.65; 0.71]	0.06	[0.06; 0.07]
Nest parameter	σ_{kg}	6.81	[6.82; 7.49]	1.09	[1.09; 1.09]

This table presents the main estimates of the labor supply parameters. The "average" of any parameter is defined as the employment-weighted average in the data (see Section **??**). Panel A reports the average estimates for the entire sample. Panel B reports the estimates for native-born workers only. Panel C reports the estimates for immigrants only. The parameter β_k represents the marginal utility of the wage in the utility function (see equation 1). The parameter σ_{kg} is the "nest parameter" related to the correlation of idiosyncratic preferences within a labor market (see section 3.2). Both IV and Ordinary Least Squares (OLS) estimates are reported, with 95% bootstrap confidence intervals (Hall 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table A3: Correlations of estimated amenities with illness or injury

Dependent variable: $\log(u_{kjt})$		
	(1)	(2)
Cases	-0.066	-0.072
	(0.028)	(0.098)
Immigrant		0.411
		(0.306)
Immigrant $\times$ Cases		0.007
		(0.103)
Observations	520	520
R-squared	0.01	0.022

This table presents results from the estimation of equation 13. The dependent variable is $\hat{\psi}^{u}_{kn}$, which are the estimated industry fixed effects from the regression of vertical amenities on firm characteristics (see equation 12). The dependent variable "cases" refers to the cases of illness or injury per 100,000 people. Column (1) shows the simple linear regression of equation 13. Column (2) shows the results from a similar regression model that includes an interaction of cases with immigrant status. *Source:* Author's calculations from the Canadian Employer-Employee Dynamics Database (CEEDD) and The U.S. Bureau of Labor Statistics Data on Injury, Illness, and Fatalities.

B Additional Details on the Economic Class

The *Economic Class* grants permanent residence to individuals primarily on the basis of their human capital characteristics. This class encompasses a range of federal and subnational programs designed to select applicants with skills and experience expected to contribute to the Canadian labor market. There are three main federal programs within the *Economic Class*: The *Federal Skilled Workers Program (FSWP)*, the *Canadian Experience Class (CEC)*, and the *Federal Skilled Trades Program (FSTP)*. The FSWP is a points-based system that was first introduced in 1967. Applicants to the FSWP are assigned points based on education, age, skilled work experience, proficiency in English or French, ability to integrate into Canada, and whether the applicant has a job offer from a Canadian employer. The federal government sets a minimum points threshold, and applicants who meet or exceed this threshold satisfy the program's selection criteria. In contrast to the FSWP, the CEC and FSTP evaluate applicants on a pass/fail basis. The CEC was introduced in 2008 and requires applicants to meet a minimum Canadian work experience requirement (initially two years, reduced to one year in 2012), while the FSTP was introduced in 2013 and requires applicants to have a Canadian certificate of qualification in a skilled trade or a job offer from a Canadian employer.[16]

At the subnational level, the *Provincial Nominee Program (PNP)* allows provinces and territories to design immigration streams based on local economic and demographic needs. Manitoba signed the first PNP agreement in 1996, and since then, all provinces and territories except Quebec and Nunavut have joined the program. The immigration streams in the PNP are diverse, with over 50 distinct PNP streams across 11 participating provinces and territories in 2011 (Citizenship and Immigration Canada 2011). PNP streams commonly

16. Since 2015, the FSWP, FSTP, and CEC have been centrally managed by the federal *Express Entry (EE)* system. The EE system is an application management system, not a stand-alone program. In the EE system, applicants must first meet the minimum eligibility requirements of the FSWP, FSTP, or CEC to enter the EE pool, where they subsequently receive a Comprehensive Ranking System (CRS) score. Applicants in the EE pool with CRS scores above a minimum threshold are invited to apply for permanent residency.

focus on selecting immigrants who work in high-demand occupations or have a job offer from an employer within the province. If the province or territory determines that an applicant meets the eligibility criteria of a particular stream, it formally selects the applicant for permanent residence through a process called a provincial nomination. Once nominated, the applicant receives the *Provincial Nominee Class (PNC)* designation and the federal government subsequently conducts medical, security, and criminal background checks and confirms that the applicant intends to reside in the nominating province before granting permanent residence.

The province of Quebec has its own program within the *Economic Class* that is distinct from the FSWP, CEC, FSTP, and PNP, introduced in 1991 and known as *Programme régulier des travailleurs qualifiés (PRTQ)* (replaced by *Programme de sélection des travailleurs qualifiés (PSTQ)* in 2024). This program evaluates applicants using a points-based system similar to the FSWP, but includes additional criteria for French proficiency and family connections in Quebec.

C Identification of the CKMM Model

C.1 Labor supply parameters

Identification of the model parameters follows CKMM closely. The labor supply parameters are identified using the quasi-supply function (i.e., Equation (5)). Equation (5) accounts for strategic interactions in wage-setting by directly controlling for the labor market share.[17] The remaining identification challenge is that wages and the labor market share may be correlated with *average* preferences for amenities, which are unobserved. For example, firms in desirable locations might offer lower wages because workers are willing to accept lower pay to enjoy the location. This is particularly relevant to the immigrant-native pay gap,

17. This is crucial, as the presence of strategic interactions in wage-setting violates the stable units treatment assumption (SUTVA) required to use labor demand shocks to identify labor supply parameters. See the discussion in Berger, Herkenhoff, and Mongey (2022) and Chan et al. (2024) for more details.

as immigrants may have different location preferences relative to natives (e.g., choosing to live and work in immigrant enclaves). Thus, estimating Equation (5) using Ordinary Least Squares (OLS) would result in biased estimates of β_k and σ_{kg}.

To identify β_k and σ_{kg} in equation (5), I follow CKMM and adopt an instrumental variables (IV) approach. The main assumptions are that innovations in firm productivity are persistent (the relevance condition) and that *average* preferences for amenities are fixed (the exclusion restriction). The relevance condition is testable, and indeed Section 5 shows that the F-statistics from the first stage of the IV are quite strong. The exclusion restriction, on the other hand, is fundamentally untestable. However, the assumption that *average* preferences for amenities are fixed is a common assumption in the literature (e.g., Sorkin 2018; Lamadon, Mogstad, and Setzler 2022). Moreover, it is important to note that this exclusion restriction does not preclude the firm from having chosen their amenities endogenously, as it only relates to the way that the amenities evolve *over time*.

More formally, assume that $\tilde{\gamma}_{kjt}$ follows an AR(1) process and preferences for *average* amenities $\log u_{kjt}$ can be decomposed into a component that is fixed over time and "white noise" measurement error.[18] Then, write the labor supply Equation (5) in "long changes":

$$\Delta_{long}\left[\log \frac{s_{kjgt}}{s_{k0t}}\right] = \beta_k \Delta_{long}\left[\log \frac{w_{kjt}}{w_{k0t}}\right] + \tilde{\sigma}_{kgt}\Delta_{long}\left[\log s_{kj|gt}\right] + \Delta_{long}[\log e_{kjt}], \tag{14}$$

where for variable x_{kjt}, the operator Δ_{long} indicates a "long change" over a 5-year period, i.e., $\Delta_{long}x_{kjt} = x_{kjt+2} - x_{kjt-3}$ for any variable x_{kjt}, and the error term $\log e_{kjt}$ is the measurement error. The assumptions that productivity $\tilde{\gamma}_{kjt}$ follows an AR(1) process and preferences for deterministic amenities $\log u_{kjt}$ imply that "short" (i.e., one-period) changes in productivity-related variables are valid instruments.[19] Following CKMM, I use the following variables to

18. CKMM allow for limited correlation in the measurement error over time. All of the arguments hold if we assume that the measurement error evolves according to an MA(1) process, following Lamadon, Mogstad, and Setzler (2022).

19. Formally, for any proxy for productivity z_{kjt}, the instruments are constructed as:

$$\Delta_{short}z_{kjt} = z_{kjt} - z_{kjt-1},$$

construct instruments: the log of firm revenue ($\log R_{jt}$), the log of the market share of type k workers $\log s_{kjt|g}$, and the log of the sum of the market shares of all other types at the firm $\log\left(\sum_{\{h\in C_{jt}|h\neq k\}} s_{hjt|g}\right)$.

CKMM show that these internal panel instruments generate results that are consistent with a variety of "external instruments" used in the monopsony literature to identify firm-specific labor supply parameters.[20] I choose to use internal panel instruments in this paper, rather than external instruments, because internal panel instruments can be used to identify labor supply parameters for firms in all industries and labor markets. External instruments, by contrast, can only be used to identify labor supply parameters in narrow contexts, for example the government procurement contracts in Kroft et al. (2024) (see CKMM or Lamadon, Mogstad, and Setzler (2022) for a detailed discussion).

In practice, Equation (14) is estimated using Two-Stage Least Squares (2SLS).

C.2 Labor demand parameters

Given the labor supply parameters, we can calculate the labor supply elasticity $\mathcal{E}_{kjt}$ using Equation (6) and the factor $\frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}$. Then, using the first-order condition of the firm's profit maximization problem (Equation (8)), we can identify the MRPL using:

$$\text{MRPL}_{kjt} = \frac{1+\mathcal{E}_{kjt}}{\mathcal{E}_{kjt}} w_{kjt}.$$

Next, we use the assumptions about the firm's production technology (Equation (7)) to

where the Δ_{short} operator is the change in variable z_{kjt} over one period.

20. Lamadon, Mogstad, and Setzler (2022) show that their internal instruments produce results similar to those obtained with the external instruments in Kroft et al. (2024). CKMM show that their instruments are similar to external instruments derived from export shocks (Garin and Silverio 2023; Hummels et al. 2014) and find similar results.

express the MRPL as a function of the technology parameters:

$$\text{MRPL}_{kjt} = P_{jt}\alpha_{jt}\tilde{\theta}_{jt}\gamma_{kjt}\left(\sum_{k\in C_{jt}} \tilde{\gamma}_{kjt}l_{kjt}\right)^{\alpha_{jt}-1}.$$

For any $h, k \in \{1, ..., K\}$, we can write the ratio of MRPL as:

$$\frac{\text{MRPL}_{kjt}}{\text{MRPL}_{hjt}} = \frac{\gamma_{kjt}}{\gamma_{hjt}}.$$

Then, using the normalization that $\sum_{k\in C_{jt}} \gamma_{kjt} = 1$, we have that

$$1 = \sum_{k\in C_{jt}} \frac{\gamma_{hjt}\text{MRPL}_{kjt}}{\text{MRPL}_{hjt}}$$

which implies

$$\gamma_{hjt} = \frac{\text{MRPL}_{hjt}}{\sum_{k\in C_{jt}} \text{MRPL}_{kjt}}. \tag{15}$$

The identification of γ_{hjt} is intuitive: the γ_{hjt} is identified (up to a normalization) by comparing the MRPL across different types of workers within the same firm.

To identify α_{jt}, note that we can express the MRPL for worker type k at firm j and time t as:

$$\text{MRPL}_{kjt} = \alpha_{jt}\gamma_{kjt}\frac{R_{jt}}{\sum_{h\in C_{jt}} \gamma_{hjt}l_{hjt}}, \tag{16}$$

where $R_{jt} = P_{jt}F_{jt}$ is the revenue of firm j at time t. Note that R_{jt} is observed in the data, and thus everything in Equation (16) is known except for α_{jt}. Plugging in the expression for γ_{kjt} into Equation (16) and re-arranging, we get the following equation which is used to identify α_{jt}:

$$\alpha_{jt} = \frac{\sum_{h\in C_{jt}} \text{MRPL}_{hjt}l_{hjt}}{R_{jt}}. \tag{17}$$

In words, α_{jt} is identified by comparing a linear approximation of total revenue produced by labor inputs to the observed revenue in the data.[21]

Finally, to identify TFP $\tilde{\theta}_{jt}$, we must assume perfect competition in the output market (which implies constant output price across firms, i.e., $P_{jt} = P_t$ for all j) and normalize the price of output to 1. Then, we can use the structural equation for revenue to identify TFP:

$$R_{jt} = \tilde{\theta}_{jt} \left(\sum_{k \in C_{jt}} \gamma_{kjt} l_{kjt} \right)^{\alpha_{jt}},$$

which implies:

$$\tilde{\theta}_{jt} = \frac{R_{jt}}{\left(\sum_{h \in C_{jt}} \gamma_{hjt} l_{hjt} \right)^{\alpha_{jt}}}. \tag{18}$$

D Solving for the counterfactual equilibrium

CKMM show that there is a unique equilibrium in the model and show that it is possible to use an underrelaxed Jacobi iteration algorithm to solve for counterfactual wages and employment. The algorithm is as follows. Let $w_t \equiv (w_{11t}, ..., w_{KJt})$ represent the vector of wages for all types at all firms at time t. For each $k \in \mathcal{K}$, $j \in \mathcal{J}$, and $t \in \{2002, ..., 2019\}$, define:

$$\delta_{kjt}(w_t) \equiv w_{kjt} - \tilde{\theta}_{jt} \alpha_{jt} \gamma_{jt} \left(\sum_{k \in C_{jt}} \gamma_{kjt} l_{kjt}(w_t) \right)^{\alpha_{jt}-1} \frac{\mathcal{E}_{kjt}(w_t)}{\mathcal{E}_{kjt}(w_t) + 1},$$

where $l_{kjt}(w_t)$ is the labor supply of workers of type k to firm j at time t as a function of the vector of posted wages w_t. The algorithm proceeds as follows. For $\xi \in (0, 1]$:

1. Solve $\delta_{kjt}(w^n_{11t}, ..., w^n_{k,j-1,t}, w_{kjt}, w^n_{k,j+1,t}, ..., w^n_{KJt}) = 0$ for w_{kjt}, holding all other components fixed.

2. Set $w^{n+1}_{kjt} = (1 - \xi) w^n_{kjt} + \xi w_{kjt}$ for all $kj = 11, ..., KJ$ and $t = 2002, ..., 2019$.

21. Consider the special case where $\sum_{h \in C_{jt}} \text{MRPL}_{hjt} = R_{jt}$. Then the linear approximation to revenue equals revenue exactly, implying a linear production function (constant returns to scale) and $\alpha_{jt} = 1$.

E Additional Results

E.1 Heterogeneity across provinces

There is some heterogeneity in labor supply elasticities and markdowns across provinces, with lower values observed in Quebec, the Prairies, and Atlantic Canada (see Figure A5). These results are intuitive, suggesting that workers in Ontario and British Columbia have more suitable job alternatives compared to workers in other provinces. In the Prairies and Atlantic provinces, immigrants face markdowns that are 15 percentage points lower on average than those of native-born workers, suggesting that firms exert substantially more monopsony power over immigrants in these areas. In Quebec, the markdown gap is 10 percentage points, indicating that firms also hold considerably more monopsony power over immigrant workers compared to native-born workers in Québecois labor markets. In Ontario and British Columbia, the average difference in markdowns is lower: immigrants face an average markdown that is 4 percentage points lower in Ontario and 5 percentage points lower in British Columbia.