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 from Canada, I estimate a wage-posting model that incorporates two-sided heterogeneity and strategic interactions in wage setting. In the model, firms mark down wages below the marginal revenue product of labor (MRPL), and the equilibrium immigrant-native pay gap arises from differences in wage markdowns and MRPL. The findings suggest that immigrants earn 77% of their MRPL on average, compared to 84% for natives. I also decompose the immigrant-native pay gap using counterfactual exercises that account for general equilibrium responses of workers and firms. The results of the counterfactuals suggest that (1) differences in labor supply curves contribute significantly to earnings inequality between immigrants and natives; (2) immigrants tend to work at more productive firms, driven by their tendency to work in cities where firms are more productive on average; and (3) interactions between firm productivity and labor supply are important, which implies that methodologies relying on additive separability assumptions will likely produce biased decompositions of the immigrant-native pay gap.

Keywords: Immigration, inequality, monopsony, firm productivity, immigrant-native earnings differential

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

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1 Introduction

In all 33 high-income countries recently surveyed by the International Labour Organization (ILO), immigrants earned less on average than native-born workers, with an average pay gap of 13% across countries (Amo-Agyei, 2020). Canada is no exception, despite having the highest proportion of immigrants among G7 countries and immigration policy that is explicitly designed to attract high-skilled workers.[1] According to the 2016 Canadian Census, the immigrant-native pay gap among full-time employees is roughly 16%, a gap that 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 et al., 2006), quality of schooling (Bratsberg et al., 2006; Fortin et al., 2016), job mobility (Javdani and McGee, 2018; Pendakur and Woodcock, 2010; Skuterud and Su, 2012), and discrimination (Bartolucci, 2014; Oreopoulos, 2011). In addition, recent papers that use AKM models (Abowd et al., 1999) to decompose the immigrant-native pay gap into differences in individual-level and firm-level components find that differences in firm-specific pay premiums contribute significantly (Amior & Stuhler, 2024; Arellano-Bover & San, 2024; Damas de Matos, 2017; Dostie et al., 2023; Gyetvay & Keita, 2024). However, we do not know which of the underlying mechanisms that generate firm-specific pay premiums are important for the pay gap. Firm-specific pay premiums reflect several distinct underlying factors, including firm productivity, firms' ability to mark down wages below marginal revenue product (MRPL), and compensating differentials (Card et al., 2018).[2] The existing research does not shed light on the importance of these underlying factors due to the methodological challenges associated with measuring them and the high data requirements involved.

In this paper, I examine the importance of labor market power and firm productivity for understanding the immigrant-native pay gap. My empirical analysis uses the Canadian Employer-Employee Dynamics Database (CEEDD), a comprehensive matched employer-employee dataset that includes detailed information on immigrants. Building on the frame-

[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 (see Beach et al., 2011 for a summary of the history of Canada's immigration policy).

[2] In many monopsony models, firms mark down the wage below the marginal revenue product of labor (MRPL) according to Wage $= \frac{\mathcal{E}}{1+\mathcal{E}} \times$ MRPL, where $\mathcal{E}$ is the labor-supply elasticity to the firm and $\frac{\mathcal{E}}{1+\mathcal{E}} < 1$ represents the markdown. Card et al. (2018) explain the connection between monopsony power and AKM models, illustrating that firm-specific pay premiums reflect both wage markdowns and MRPL. Additionally, the authors explain that when firms have diminishing MRPL, there are wage penalties associated with working at larger firms, and this generates compensating differentials (see Card et al., 2018 for a detailed discussion).

work in Chan et al. (2024), I estimate a wage-posting model that incorporates two-sided heterogeneity and strategic interactions in wage setting. In the model, firms endogenously mark down the wage below the marginal revenue product of labor (MRPL), and the equilibrium immigrant-native pay gap arises due to differences in wage markdowns (defined as the ratio of the wage to the MRPL) and differences in the MRPL itself. The results suggest that immigrants earn 77% of their MRPL on average, compared to 84% for natives. In addition, I decompose the immigrant-native pay gap using counterfactual analyses that take into account general equilibrium responses of workers and firms. The counterfactual analyses yield three main findings. First, differences in labor supply curves between immigrants and natives contribute significantly to the pay gap. Second, immigrants tend to work at more productive firms, driven by their tendency to work in cities where firms are more productive on average. Finally, interactions between firm productivity and labor supply are important, implying methodologies that rely on additive separability assumptions will likely produce biased decompositions of the immigrant-native pay gap.

In Section 2, I discuss the structural model, which builds on Chan et al. (2024) (henceforth CKMM). On the supply side, workers are divided into discrete types, each with heterogeneous skills and preferences. I build on the CKMM framework by including immigrants as a distinct worker type.[3] Workers have nested logit preferences and choose the employer to maximize utility, based on the employer's posted wage and the value of the employer's non-wage amenities. The worker's utility function includes two types of preferences for amenities: deterministic preferences, which are known to the firm and common to all workers of the same type, and stochastic preferences, which are unknown to the firm and vary idiosyncratically across individuals. On the demand side, there are a finite number of heterogeneous firms that post wages to maximize profits. The production technology assumes that worker types are perfect substitutes but allows for rich heterogeneity in match-specific productivity (Roy sorting), total factor productivity (TFP), and returns to scale. Firms face upward-sloping labor supply curves for each worker type due to oligopsonistic competition and limited information about workers' preferences, resulting in equilibrium wages that depend on endogenous wage markdowns and the MRPL.[4]

In Section 3, I discuss the identification of the structural model, which follows CKMM closely. To identify the labor supply parameters, I use the Berry (1994) quasi-supply function.[5] The quasi-supply function directly controls for the firm's labor market share to account

[3]I divide workers into types based on their gender, immigration category (economic class, family class, and refugees), and macroregion (Europe, Africa, Asia, and Americas). Based on the classification of advantaged countries in Dostie et al. (2023), I group the U.S., Australia, and New Zealand with European countries.

[4]In particular, firms lack information about workers' idiosyncratic preferences, and this generates wage-setting power. This mechanism is discussed in Lamadon et al. (2022).

[5]The Berry (1994) quasi-supply function expresses the labor quantity supplied to the firm as a function

for strategic interactions in wage setting. The remaining identification problem is that deterministic preferences for amenities may be correlated with the wage or labor market share. To overcome this identification challenge, I follow CKMM by using an instrumental variables (IV) approach similar to Lamadon et al. (2022). The key identifying assumptions are that innovations in firm productivity are persistent, while innovations in workers' deterministic preferences for non-wage amenities are transitory. To identify the production function, I use the first-order condition (FOC) for firm profit maximization, which depends on the labor-supply elasticities identified in a previous step.

In Section 4, I describe the data used in the empirical analysis. The model is estimated using the Canadian Employer-Employee Dynamics Database (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 also 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, allowing for the estimation of labor demand.[6] To select the subset of individuals and firms for the analysis, I follow Dostie et al. (2023) closely, ensuring that my results contribute directly to the literature on firm-specific pay premiums and their role in the immigrant-native earnings gap.

In Section 5, I discuss the main estimates of the model parameters. The average labor supply elasticity in Canada is 5.25, consistent with credible findings from other countries where elasticities typically range between 3 and 6 (Card, 2022; Manning, 2021).[7] Through the lens of the model, this average elasticity implies an average wage markdown of 82%, meaning that workers tend to earn 82% of their MRPL. There is a notable gap in labor-supply elasticities and markdowns between immigrants and natives. Natives have an average elasticity of 5.45 (markdown 84%), compared to an elasticity of 4.45 for immigrants (markdown 77%). When analyzing heterogeneity across different immigrant groups, refugees and family-class immigrants tend to have more inelastic labor supply compared to immigrants in the economic class. Economic-class immigrants have a labor-supply elasticity of 5.09, which is higher and statistically different from the labor-supply elasticities for family-class

of the wage and labor market share.

[6]Other datasets commonly used in studies of the immigrant-native earnings gap and monopsony power, such as the German data (see Amior and Stuhler, 2024; Gyetvay and Keita, 2024), lack financial information on firms and therefore cannot be used to estimate labor demand for immigrants and natives.

[7]In the model, the labor-supply elasticities and wage markdowns vary across firms due to the presence of strategic interactions in wage-setting. I measure the degree of labor market power by calculating average labor-supply elasticities and markdowns, where the averages are calculated as employment-weighted averages in the data.

immigrants (3.85) and refugees (3.20). The labor-supply elasticity for economic immigrants implies a markdown of 80%, which is higher and statistically different from the markdowns for family class immigrants (75%) and refugees (73%).

Additional results discussed in Section 5 provide insight into the source of immigrants' differential exposure to labor market power. Immigrants' labor supply to the firm is more inelastic relative to natives', even after conditioning on a firm's labor market share. This finding suggests that preference heterogeneity contributes to labor supply differences between the two groups. Moreover, the estimates of the labor supply parameters imply that immigrants view firms as less substitutable compared to natives, suggesting that firms' greater labor market power over immigrants stems from immigrants having fewer suitable job alternatives. To investigate the determinants of worker preferences, I focus on the role of location and industry preferences, finding that location is considerably more important for immigrants than for natives.[8] To formally link these location preferences to labor market power, I analyze immigrants' differential exposure to labor market concentration. Following the methodology of CKMM, I decompose labor market concentration into "within-market" and "between-market" components using a generalized concentration index. The results show that immigrants are exposed to more "between-market" concentration compared to natives, a direct consequence of immigrants' strong geographic preferences.

In Section 6, I discuss the counterfactual analyses used to decompose 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 the same value for all workers (typically the mean or median in the data). Then, I predict the effects on wages and employment by solving for the counterfactual equilibrium.[9] Importantly, this approach incorporates general equilibrium responses, including any adjustments in wage markdowns, marginal products of labor, or the distribution of workers across firms. 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.

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. I demonstrate this in a counterfactual experiment in which immigrants and natives have the same

[8] These results are consistent with the large literature on immigrant enclaves, e.g. Card, 2001.

[9] Chan et al. (2024) show that there is a unique equilibrium in the model, justifying this approach.

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.[10] In this counterfactual scenario, the immigrant-native pay gap is approximately 14 percentage points lower than the true immigrant-native pay gap, illustrating the importance of differences in labor supply for earnings inequality between immigrants and natives.

Second, differences in firm productivity exacerbate 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 is approximately 13 percentage points higher compared to the true pay gap. This counterintuitive 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 scenario, the immigrant-native pay gap decreases by approximately 14 percentage points relative to the true pay gap. 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 counterfactual analyses demonstrate that interactions between firm productivity and labor supply are important for the immigrant-native pay gap. For example, the impact of worker preferences on the pay gap depends heavily on firm productivity differences. Equalizing the distribution of idiosyncratic preferences for amenities across immigrants and natives reduces the pay gap by 14 percentage points, as described above. However, if we first eliminate TFP differences across firms, the same adjustment to preferences reduces the gap by only 4 percentage points, demonstrating significant interaction effects. By taking into account general equilibrium responses when solving for the counterfactual wages and employment, the decompositions allow for rich interactions between the different factors that generate pay inequality between immigrants and natives.

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 & Manning, 2020; Depew et al., 2017; Hirsch & Jahn, 2015; Hunt & Xie, 2019; Naidu et al., 2016; Wang, 2021). A particularly relevant study is Hirsch and Jahn

[10] Intuitively, differences in the distribution of idiosyncratic preferences across immigrants and natives capture the extent to which immigrants and natives differ in their outside options. The results in Section 5.1.1 show that natives view firms as more substitutable compared to immigrants, implying that natives have more suitable job alternatives relative to immigrants. Fewer suitable job alternatives lead to more inelastic labor supply and more labor market power for firms, as described in Section 2.2.

(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, in addition to examining the importance of labor market power, it also examines the importance of firm productivity and interactions between firm productivity and heterogeneity in labor supply. Second, it introduces a novel approach to decomposing the pay gap in a general equilibrium framework – an approach to understanding the immigrant-native pay gap that, to my knowledge, has not been explored in the existing literature.

2 Model

2.1 Set up

Heterogeneous workers are categorized into discrete types, where each worker i has type $k \in \mathcal{K}$. I consider 26 different k-groups of workers. As suggested in the literature on labor market power and the gender gap (Robinson, 1933; Sharma, 2024; Webber, 2016), there may be important differences in labor supply between men and women, and therefore I divide workers into types based on gender. Canada's immigration system categorizes workers into economic-class immigrants, family-class immigrants, and refugees, all of which may have different labor-supply curves and/or differences in skills, and therefore I also classify immigrant workers based on their immigration category.[11] Finally, there is evidence in the literature of heterogeneous returns to education and experience by source country (see, e.g. Fortin et al., 2016), and therefore I also classify workers based on continent of origin (Europe, Africa, Asia, and Americas).[12]

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 as 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.

[11] The analysis focuses on immigrants who are permanent residents and excludes temporary foreign workers. In addition, note that individuals other than the principal applicant may be classified as economic-class immigrants in the data. However, in the sample used for the main analyses, the majority of individuals categorized as economic-class immigrants are principal applicants.

[12] I group immigrants from the U.S., Australia, and New Zealand with immigrants from Europe, following Dostie et al. (2023)'s definition of "advantaged" immigrants. I group Mexico with the Americas.

2.2 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, $u_{kjt} > 0$ represents the deterministic preference for amenities at firm j common to all workers of type k at time t, and ε_{ijt} captures the stochastic preference over the amenities at firm j at time t which is idiosyncratic 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 stochastic preference ε_{ijt} is assumed to follow a nested logit distribution with the 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 $\frac{1}{\sigma_{kg}} = \sqrt{1 - \text{corr}(\varepsilon_{ijt}, \varepsilon_{ij't})}$ for $j, j' \in \mathcal{J}_g$. The parameter σ_{kg} measures the correlation of the stochastic preferences for firms within the same market.

This utility specification allows for firms to be imperfect substitutes. There are two components of job differentiation in the model: vertical differentiation, captured by $\log(u_{kjt})$, representing the common value of working at firm j at time t for all workers of type k; and horizontal differentiation, captured by ε_{ijt}, reflecting idiosyncratic worker preferences. Both vertical and horizontal differentiation contribute to labor market power. Firms with high u_{kjt} will attract more workers, thereby increasing their size and labor market power. A higher degree of horizontal differentiation within a labor market also increases labor market power. When firms are less substitutable (i.e., when there is more horizontal differentiation), workers have fewer desirable job alternatives and firms are able to post lower wages.

The degree of horizontal differentiation for workers of type k in labor market g is governed by the parameters σ_{kg} and β_k. 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 are viewed as perfect substitutes. Thus, as σ_{kg} increases, firms become more similar from the worker's perspective, implying that workers perceive more suitable job alternatives. Consequently, a higher σ_{kg} lowers the labor market power of firms. The parameter β_k represents the marginal utility of wages and measures the relative importance of wages compared to amenities. A higher β_k suggests that wages are more important for the worker compared to amenities. Thus, a higher β_k implies that firms are more substitutable and therefore lowers firms' labor market power.

The labor supply parameters are likely to differ between non-immigrants and immigrants from various backgrounds. Firms that offer immigrant-friendly work environments may have a higher u_{kjt} for immigrant workers. These firms will grow in size as a result of their desirable work environment and gain monopsony power over immigrants as a result. The degree of horizontal differentiation in a labor market (captured by the preference parameters β_k and σ_{kg}) is also expected to differ across non-immigrants and immigrants of various backgrounds. For example, a common source of horizontal differentiation in labor markets that generates monopsony power is commuting distance (Manning, 2021). It is well-known in the immigration literature that immigrants prefer to live in ethnic enclaves.[13] Thus, the degree of horizontal differentiation for different immigrant groups depends in part on the commuting distance between the ethnic enclaves and employers who hire immigrants.

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:

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

The derivative of $G_{k.}(v_{k.t})$ with respect to v_{kjt} can be calculated from equation 2.2 and substituted into equation 3 to obtain the labor supply function for type k workers at firm j at time t. Following Berry (1994), in the empirical analysis I use the *quasi*-supply function, defined as the ratio of the log of the supply function of type-k workers to firm j at time t divided by the supply function for the outside option (non-employment) for type-k workers

[13] This has been exploited in various papers studying the effects of immigration. For example, see Altonji and Card (1991) and Card (2001).

at time t:

$$\log \frac{s_{kjt}}{s_{k0t}} = \beta_k \log \frac{w_{kjt}}{w_{k0t}} + \tilde{\sigma}_{kg} \log s_{kjt|g} + \log u_{kjt}, \tag{4}$$

where $\frac{s_{kjt}}{s_{k0t}}$ is the ratio of firm j's share of type-k workers to the share of type-k workers who are non-employed in period t, $\frac{w_{kjt}}{w_{k0t}}$ is the ratio of the wage paid to type-k workers by firm j relative to unemployment benefits in period t, and $s_{kjt|g}$ is the labor market share (sometimes called the "inside share"), which is the firm's share of type-k employment in the local labor market g at time t. The parameter $\log u_{kjt}$ represents the deterministic preference for amenities common to all workers of type k at firm j in period t, and $\tilde{\sigma}_{kg}$ is a transformation of σ_{kg}, i.e., $\tilde{\sigma_{kg}} = (1 - 1/\sigma_{kg})$.

It is possible to express the labor supply elasticity as:

$$\mathcal{E}_{kjt} = \beta_k \sigma_{kg} + \beta_k [(1 - \sigma_{kg}) s_{kjt|g} - s_{kjt}], \tag{5}$$

Equation 5 shows that the labor supply elasticity is a function of β_k, σ_{kg}, local labor market share $s_{kjt|g}$, and the fraction of all workers at the firm s_{kjt}. The expression shows that when β_k and σ_{kg}, which imply more horizontal differentiation for workers of type k, are lower, then labor supply is more inelastic, i.e., $\mathcal{E}_{kjt}$ is lower. A lower $\mathcal{E}_{kjt}$ implies a lower markdown (see equation 7), indicating a higher degree of labor market power.[14] Equation 5 also shows that labor-supply elasticities vary at the firm level due to variation in labor market shares across firms.

2.3 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 $l_{\cdot jt} \equiv (l_{1jt}, \ldots, l_{Kjt})$ is the vector of labor inputs at firm j at time t. Let $F_{jt}(l_{\cdot jt})$ 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:

$$F_{jt}(l_{\cdot jt}) = \left(\sum_{k \in C_{jt}} \tilde{\gamma}_{kjt} l_{kjt} \right)^{\alpha_{jt}}, \tag{6}$$

where $\tilde{\gamma}_{kjt} \equiv \theta_{jt}\gamma_{kjt}$ with $\sum_{k \in C_{jt}} \gamma_{kjt} = 1$. The parameter $\tilde{\theta}_{jt} \equiv \theta_{jt}^{\alpha_{jt}}$ represents total-factor productivity (TFP) of firm j at time t, the parameter α_{jt} captures the returns to scale of the production function, and the parameter γ_{kjt} represents the relative productivity of workers

[14] If $\beta_k \to \infty$ or $\sigma_{kg} \to \infty$, we have perfect competition in the labor market.

within the same firm.[15]

This production technology allows for substantial heterogeneity in productivity across periods, firms, and different worker types. It also allows for production complementarities between workers and firms, which have been shown to be important in the literature (see Lamadon et al., 2022; Taber and Vejlin, 2020). We expect immigrants in different immigration categories (e.g., economic class, family class, refugees) to exhibit varying productivity levels, as economic immigrants typically possess higher levels of education and experience compared to other immigrant groups and native-born workers. Additionally, productivity differences may arise among immigrants from different world regions due to varying returns to education or experience across countries (see Fortin et al., 2016).

The production technology also implies that workers are perfect substitutes. The assumption of perfect substitutes in production is common in the monopsony literature (see Chan et al., 2024; Lamadon et al., 2022). Specifically, Chan et al. (2024) test for imperfect substitution among different worker types and find that a perfect-substitutes production function approximates the production process quite 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.[16] Formally, in period t, firm j chooses the vector of wages $\vec{w}_{jt}$ to maximize

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

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 firm j's labor demand for workers of type k at time t can be rearranged as follows:

$$w_{kjt} = \underbrace{P_{jt}\frac{\partial F_{jt}(l_{.jt})}{\partial l_{kjt}}}_{\text{MRPL}_{kjt}} \times \underbrace{\frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}}_{\text{md}_{kjt}}, \tag{7}$$

where $\mathcal{E}_{kjt} = \frac{\partial l_{kjt}}{\partial w_{kjt}} \frac{w_{kjt}}{l_{kjt}}$ represents the labor supply elasticity of type k to firm j at time t, the term MRPL_{kjt} is the marginal revenue product of labor for worker type k at firm j at time t, and the term md_{kjt} is the markdown for worker k at firm j at time t.

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

[16] There is a unique equilibrium wage vector in the Bertrand-Nash equilibrium.

2.4 Employment-weighted Averages

In the remainder of the paper, I discuss several averages of model parameters across immigrants and natives (and various subgroups of immigrants). These are employment-weighted averages, defined precisely below.

Recall that we have 26 different "k-types" denoted by $k \in \mathcal{K}$ (see section 2.1). For any subset $\mathcal{S} \subset \mathcal{K}$ (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. The main subgroups I consider are natives and immigrants, but I also discuss averages for some subgroups of immigrants, e.g. those from the economic class, family class, or refugees.

Using the above notation, the pay gap between immigrants and natives is defined as:

$$\text{Pay Gap} \equiv \frac{\overline{w}_{k\in\text{Native}} - \overline{w}_{k\in\text{Immigrant}}}{\overline{w}_{k\in\text{Native}}},$$

where $\overline{w}_{k\in\text{Immigrant}}$ is the average wage of immigrants in the data, and $\overline{w}_{k\in\text{Native}}$ is the average wage of natives in the data.

3 Identification

3.1 Labour supply parameters

The labor supply parameters are identified using the quasi-supply function (i.e., equation 4). Using equation 4, it is possible to account for oligopsony and 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 deterministic preferences for amenities, which are unobservable. 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, as immigrants may have different location preferences compared to non-immigrants (e.g., choosing to live and work

[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 et al. (2022) and Chan et al. (2024) for more details.

in immigrant enclaves). Thus, estimating equation (4) 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 (4), I follow CKMM and adopt an instrumental variables (IV) approach using "internal panel instruments" similar to Lamadon et al. (2022). The main assumptions are that innovations in firm productivity are persistent, while innovations in workers' deterministic preferences for amenities are transitory. Importantly, these assumptions place restrictions on how the productivity and amenities processes evolve over time, but they do *not* place restrictions on the relationship between the average levels of productivity and amenities. In particular, the assumptions do not preclude the firm from having chosen the average level of amenities endogenously.

More formally, following CKMM and Lamadon et al. (2022), assume that productivity $\tilde{\gamma}_{kjt}$ follows an AR(1) process and preferences for deterministic amenities $\log u_{kjt}$ follow an MA(1) process. Then, write the labor-supply equation 4 in "long changes":

$$\Delta_{long}\left[\log\frac{s_{kjgt}}{s_{k0t}}\right] = \beta_k\Delta_{long}\left[\log\frac{w_{kjt}}{w_{k0t}}\right] + \tilde{\sigma}_{kgt}\Delta_{long}\left[\log s_{kj|gt}\right] + \Delta_{long}[\log u_{kjt}], \tag{8}$$

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}. 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.[18] Following CKMM, I use the following variables to construct instruments: 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 $\log\left(\sum_{\{h\in C_{jt}|h\neq k\}} s_{hjt|g}\right)$.

With the assumption that $\log u_{kjt}$ follows an MA(1) process and that productivity $\tilde{\gamma}_{lkjt}$ follows an AR(1) process, the changes in productivity variables will be correlated with long changes in wages and the market share but uncorrelated with long changes in workers' deterministic preferences for amenities. This ensures that the exclusion restriction and relevance condition hold, identifying β_k and σ_{kg}. CKMM and Lamadon et al. (2022) provide evidence that the identification assumptions hold and show that these instruments generate results that are consistent with a variety of "external instruments" used in the monopsony literature to identify firm-specific labor-supply parameters.[19] I choose to use internal instruments

[18]Formally, for any proxy for productivity z_{kjt}, the instruments are constructed as:

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

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

[19]Lamadon et al. (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

in this paper, rather than external instruments, because internal 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 Chan et al. (2024) or Lamadon et al. (2022) for a detailed discussion).

In practice, equation 8 is estimated using Two-Stage Least Squares (2SLS).

3.2 Labor demand parameters

Given the labor supply parameters, we can calculate the labor-supply elasticity $\mathcal{E}_{kjt}$ using equation 5 and the markdown md_{kjt} using the equation $\text{md}_{kjt} = \frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}$. Then, using the first order condition of the firm's profit maximization problem (equation 7), we can identify the marginal revenue product of labor (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 6) to 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

$$\gamma_{hjt} = \frac{\text{MRPL}_{hjt}}{\sum_{k\in C_{jt}} \text{MRPL}_{kjt}}. \tag{9}$$

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

similar results.

firm.

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

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

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 10 is known except for α_{jt}. Plugging in the expression for γ_{kjt} into 10 and re-arranging, we get the following equation which is used to identify α_{jt}:

$$\alpha_{jt} = \frac{\sum_{h\in C_{jt}}\text{MRPL}_{hjt}l_{hjt}}{R_{jt}}. \tag{10}$$

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.[20]

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:

$$\tilde{\theta}_{jt} = \frac{R_{jt}}{\left(\sum_{h\in C_{jt}}\gamma_{hjt}l_{hjt}\right)^{\alpha_{jt}}}. \tag{11}$$

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 ori-

[20]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 $\alpha_{jt} = 1$.

gin and immigration category.

Data cleaning closely follows the methodology outlined in Dostie et al. (2023) and Li et al. (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 premiums and their role in the immigrant-native earnings gap.[21]

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.

Firms in the public sector (NAICS 91), education (NAICS 61), and health sectors (NAICS 62) are excluded from the analysis. 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 specific labor market details such as hourly wages and hours worked. To address this, the sample is narrowed to full-time equivalent (FTE) workers, defined as those earning at least approximately $18,000 in 2012 dollars.[22] Moreover, individuals in the CEEDD may have multiple T4 records if they hold multiple jobs. To manage this, the analysis is restricted to each individual's primary job, defined as the job that provides the highest income in any given year.

Labor markets are defined following Lamadon et al. (2022) as combinations of 2-digit NAICS codes and geographic locations. Geographic locations are based on Census Metropolitan Areas (CMAs) or Census Agglomerates (CAs) as defined in the 2016 Census of Population. CMAs and CAs consist of population centers and adjacent municipalities with high commuting flows, resembling U.S. commuting zones. 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

[21] Dostie et al. (2023) estimate an AKM model using the CEEDD to decompose the immigrant-native earnings gap into individual-level and firm-level components. I mainly follow Dostie et al. (2023), only departing from their procedures when I define full-time equivalent (FTE) workers, which I obtain from Li et al. (2023).

[22] The FTE threshold is calculated by adjusting the minimum wage of $10.07 to 2012 dollars and multiplying by an average full-time work schedule of 38.8 hours per week over 48 weeks, following Li et al. (2023).

location data reflect the headquarters' location. For multi-location firms, each firm-location 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 firm-level revenue associated with the Enterprise ID as an instrument for the IV estimation described in section 3.)

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. 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, the the average share immigrant coworkers is only 11%. Additionally, wile 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 firms that hire both immigrants and natives tend to pay more on average (roughly $72,000 for natives and $56,000 for immigrants), compared to firms that only hire natives or only hire immigrants (roughly $55,000 for natives and $42,000 for immigrants).

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

5 Results

5.1 Model Primitives

5.1.1 Labor Supply

Before discussing the main estimates of the labor supply parameters, I begin by discussing the relevance condition associated with the IV approach used to estimate them. As mentioned in section 3, 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 productivity-related variables are strongly correlated with long changes in wages and market shares.[23] Most F-statistics exceed 10, with the majority surpassing 100.

[23] 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). Given that β_k varies only by worker type, the assumption about σ_{kg} means the distribution of stochastic preferences is the same for all local labor markets within a specific worker type-province group combination. The main results are similar if I instead assume that σ_{kg} is constant

Only 3 out of 26 k-types have an F-statistic below 10 for β_k, representing less than 1% of the full sample and less than 3% of all immigrants.[24]

The main estimates of the labor-supply parameters indicate that the distribution of stochastic preferences for amenities differs between immigrants and natives. Table 2 presents employment-weighted averages of the estimated labor supply parameters β_k and σ_{kg} for immigrants and natives, with confidence intervals calculated using the bootstrap estimator from Hall (1992).[25] A lower β_k and a lower σ_{kg} both contribute to increased horizontal differentiation, generating labor market power (see equation 5). We find that immigrants have a higher average β_k (0.70) compared to natives (0.56), and this difference is statistically significant. Conversely, immigrants have a lower average σ_{kg} (6.81), compared to natives (11.73), a statistically significant difference.[26] Figure A1 displays the values of β_k and figure A2 displays the average σ_{kg} for each k-group.

Table 2 also shows that the OLS estimates of the labor supply parameters are downward biased in the full sample and for the immigrant and native subgroups. Figure A3 presents the OLS estimates of the labor supply parameters by worker type k.

5.1.2 Labor Demand

We turn now to estimates of the labor demand parameters, which are summarized in Table 4. The labor demand parameters can be categorized into two groups: the "between-firm" 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 "within-firm" parameters γ_{kjt} (which vary across worker types within the same firm). First, we examine the between-firm parameters. The average value of the returns to scale parameter α_{jt} across the full sample is 0.26, indicating generally decreasing returns to scale for firms.[27] Comparing immigrants and natives, we find that both of the firm-level productivity parameters tend to be slightly higher for immigrants compared to

within each unique combination of type k and the 10 provinces or if I assume that σ_{kg} is constant within each unique combination of type k and 2-digit NAICS industry codes. Due to computational challenges estimating the model (especially for bootstrapping confidence intervals), and since the results are robust to alternate assumptions about the variation in σ_{kg} (as long as we allow σ_{kg} to vary across type k), I present results where σ_{kg} is constant within each unique combination of worker type k and the 4 province groups.

[24] The results are similar if these three k-types are removed from the analysis or grouped with other categories.

[25] As discussed in Section 2.4, I present employment-weighted averages of the model primitives. For any model primitive $x_{kjt} \in \{\beta_k, \sigma_{kg}, \alpha_{jt}, \theta_{jt}, \gamma_{kjt}\}$, I calculate the average value for immigrants, natives, or various immigrant subgroups using the definition in equation 2.4.

[26] 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.

[27] This is similar to the average values of the returns to scale parameters found in Chan et al. (2024) and Lamadon et al. (2022).

natives, a result that is entirely due to sorting across firms. Immigrants have an average α_{jt} of 0.27, compared to 0.25 for natives. These two values are quite similar, although the difference is statistically significant. The average $\log\tilde{\theta}_{jt}$ is slightly higher for immigrants on average (16.54) compared to natives (15.85), a small but statistically significant difference. There are also interesting patterns in TFP across different subgroups. As shown in Figure 4, we see that economic-class immigrants sort into firms with the highest TFP on average, followed by native-born workers, refugees, and family-class immigrants. Figure A4 displays the average α_{jt} and Figure A5 displays the average $\log(\tilde{\theta}_{jt})$ for each k-group.

The within-firm 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 within-firm productivity between immigrants and natives, I estimate the following regression:

$$\log(\hat{\gamma}_{kjt}) = \Gamma_k + \psi_{jt} + e^{\gamma}_{kjt}, \tag{12}$$

where $\hat{\gamma}_{kjt}$ are the estimated within-firm productivity parameters, Γ_k are worker-type fixed effects, ψ_{jt} are firm-by-year fixed effects, and e^{γ}_{kjt} is the error term. The regression results are reported in Figure A6, with female native-born workers as the omitted category.

5.2 Firm-specific Labor Supply Elasticities and Markdowns

Given the labor-supply parameters β_k and σ_{kg}, we can calculate firm-specific labor-supply elasticities using equation 5. The results, presented in Table 3, suggest a considerable amount of wage-setting power in Canada, with the average labor-supply elasticity equal to 5.25.[28] The results also suggest that immigrants' labor supply is more inelastic compared to natives. Figure 1 shows that the average labor supply elasticity for immigrants (4.42) is lower and statistically different from the average labor supply elasticity for natives (5.45).[29]

Figure 3 shows heterogeneity in labor supply elasticities across immigration categories, with those in the economic-class having the highest labor supply elasticity among immigrants (5.09), followed by family-class immigrants (3.85) and refugees (3.20). All three of these estimates are statistically significant from each other, although the average labor supply elasticity for the economic class is not statistically different from the average labor supply

[28] This estimate aligns with the existing literature that estimates firm-specific labor supply elasticities to range between 3 and 6 (Card, 2022; Manning, 2021; Sokolova and Sorensen, 2021).

[29] Similar to Section 5.1, I present employment-weighted averages of the labor supply elasticities and markdowns. These averages are calculated for immigrants, natives, or various immigrant subgroups, using the definition in Equation 2.4. Given the definition of the earnings gap, as discussed in Section 2.4, these employment-weighted averages provide a natural way to present the results.

elasticity for natives. The ordering of labor supply elasticities across immigration categories is intuitive, suggesting that refugees supply labor more inelastically relative to family-class immigrants, who supply labor more inelastically relative to those in the economic class.

Figure A7 displays the labor-supply elasticities for each k-group. Native-born men have an average labor-supply elasticity of 5.64, which is higher than and statistically different from the average labor supply elasticity of 5.09 for native-born women. This suggests that monopsony power matters for the gender earnings gap, consistent with the literature (Sharma, 2024; Webber, 2016) and Robinson's (1933) hypothesis. Additionally, certain highly skilled immigrant groups, such as those from Europe, exhibit notably low elasticities. This may be due to the highly differentiated labor markets they participate in, as indicated by their low β_k and average σ_{kg} in Figures A1 and A2. These workers tend to prioritize firm-specific amenities (as indicated by relatively low β_k) and have fewer job alternatives in the same market (as indicated by relatively low σ_{kg}), making their labor supply more inelastic.

Using the model, we can translate these elasticities into markdowns to quantify the effect of labor market power on wages using equation 7. The results in Table 3 suggest that workers receive 82% of their marginal revenue product of labor (MRPL) on average as wages. There is considerable heterogeneity across immigrant status, with native-born workers receiving 84% of their MRPL as wages on average, compared to immigrants who receive 77% on average, leading to a statistically significant markdown gap of approximately 7 percentage points (see Figure 1).

Looking at the heterogeneity by immigration category in Figure 3, we find that economic class immigrants have an average markdown of 0.80, family class immigrants have a markdown of 0.75, and refugees have a markdown of 0.73, all statistically significantly different from one another. These differences in markdowns mirror the ordering of the labor supply elasticities across the different immigration categories, as discussed above. Figure A8 displays the markdowns for each k-group.

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 A9). These results are intuitive, suggesting that workers in Ontario and British Columbia have more suitable job alternatives compared to workers in other provinces.[30] 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

[30] Ontario and British Columbia tend to have larger labor markets, with greater job alternatives for workers.

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.

5.3 Sources of Labor Market Power

5.3.1 Labor Market Concentration

With strategic interactions in wage-setting, firms gain additional labor market power when they grow in size. This relationship between market share and labor market power is evident in Figure 5, which shows that firms with larger market shares face lower firm-specific labor supply elasticities and therefore possess greater labor market power. This pattern holds for both immigrants and natives.

When firms have larger market shares, labor markets are more concentrated. To study the contribution of labor market concentration to the immigrant-native pay gap, I follow CKMM and use a generalized concentration index (GCI) that can be decomposed into within-market and between-market concentration components. Note that, in the nested logit model, a higher GCI implies lower welfare, and so these concentration indices have a direct welfare interpretation.[31] The GCI has the form:

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

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.

Figure 6 shows that immigrants are exposed to greater between-market concentration (BGCI) relative to natives. This arises because immigrants have strong geographic preferences (e.g., most immigrants in Canada settle in Vancouver, Toronto, or Montreal). Conversely, immigrants are exposed to less within-group concentration (WGCI) compared to natives, as the labor markets where immigrants are concentrated tend to be less concentrated themselves (e.g., markets with many firms, each holding smaller shares). Overall, the

[31] See Chan et al. (2024) for more information. The widely used Herfindahl-Hirschman Index (HHI) is not linked to welfare in the same way and cannot be decomposed into within-market and between-market concentration.

BGCI dominates the WGCI, leading to immigrants being exposed to more overall concentration (GCI) relative to natives.

5.3.2 Job Differentiation and Correlates of Worker Preferences

When jobs are highly differentiated, workers have fewer suitable job alternatives, and firms gain labor market power as a result. Figure 5 shows that, conditional on labor market share, immigrants supply labor more inelastically compared to natives.[32] This suggests that jobs are more differentiated for immigrants relative to natives, and that job differentiation contributes to immigrants' differential exposure to labor market power.

There are two types of job differentiation in the model: vertical differentiation and horizontal differentiation. Vertical differentiation is driven by workers' deterministic preferences for amenities. Using the model, we can gain insight into the factors that are correlated with the deterministic preferences for firm amenities. Using the estimates of β_k and σ_{kg}, it is possible to use equation 4 to estimate type-k workers' deterministic preferences for amenities at firm j at time t:

$$\widehat{\log u_{kjt}} = \log \frac{s_{kjt}}{s_{k0t}} - \hat{\beta}_k \log \frac{w_{kjt}}{w_{k0t}} - \widehat{\tilde{\sigma_{kg}}} \log s_{kjt|g}. \tag{13}$$

To investigate which factors are correlated with the deterministic preferences, I estimate the following regression:

$$\widehat{\log u_{kjt}} = X_{jt}'\beta^u + \psi_n^u + \psi_p^u + e_{kjt}^u, \tag{14}$$

where $\widehat{\log u_{kjt}}$ are the estimated deterministic preferences for amenities obtained from equation (13), X_{jt} represents firm-level characteristics (e.g., firm revenue, firm size, total wage bill), β^u is a vector of coefficients, ψ_n^u are industry-level fixed effects (with the two-digit NAICS code of the industry denoted by n), ψ_p^u are province fixed effects, and e_{jt}^u is an error term.

I estimate equation 14 separately for immigrants and natives to investigate how immigrants' deterministic preferences for amenities differ systematically from natives' deterministic preferences. The results, presented in Figure A10, suggest that immigrants have stronger deterministic preferences for living in particular locations relative to native-born workers. In the regression, the coefficients are normalized due to the omitted categories when estimating fixed effects (Newfoundland and Labrador for the province fixed effects, and Agriculture, Forestry, Fishing, and Hunting for the industry fixed effects). Thus, it is not possible to compare the coefficients for immigrants and non-immigrants directly. However, in Figure A10, we see that there is more dispersion in the province fixed effects for immigrants relative to natives, suggesting that provinces are more important for immigrants' deterministic

[32] This is evident by the vertical distance between the lines in the figure.

preferences. The distribution of coefficients for industry effects and the other covariates are similar across the two groups, suggesting that these other characteristics are less important for the immigrant-native pay gap compared to locations.

A common amenity discussed in the literature on compensating differentials is the risk of illness or injury on the job. To investigate how deterministic preferences for amenities correlate with the risk of illness or injury on the job, I estimate equation 14 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:

$$\hat{\psi^{u}_{kn}} = \eta_0 + \eta_1 x_n + \nu^u_{kn}, \tag{15}$$

where $\hat{\psi^{u}_{kn}}$ is the industry fixed effect for industry n obtained from estimating equation 14 with the deterministic preferences from worker type k, x_n is the rate of illnesses or injuries in industry n, and ν^u_{kn} is the error term.[33] The results, reported in Table A2 (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 (e.g. see 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 A2 (Column 2) suggest that there is no significant difference in the value of working in a risky environment for immigrants compared to natives.

To assess the significance of each characteristic on the right-hand side of equation 14 for deterministic preferences, I group the characteristics into three main categories: firm-level characteristics, province fixed effects, and industry fixed effects. I then examine how much of the variation in deterministic preferences is explained by each category. This is done through an "incremental R-squared" analysis, as follows.

First, I estimate equation 14 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 $\log(u_{kjt})$ explained by the excluded covariates and provides a useful metric for evaluating their explanatory power.

Figure 7 shows that province fixed effects explain a larger share of the variance in preferences for immigrants compared to natives. This finding is consistent with immigrants

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

having a strong preference for specific locations, which aligns with the literature on immigrant enclaves (Altonji and Card, 1991; Card, 2001). Figure 7 also indicates that industry fixed effects, on average, explain a smaller share of the variance in preferences for immigrants relative to natives, although the difference is much smaller compared to the difference for province fixed effects. This result is intuitive, given that immigrants tend to be more flexible regarding industry and often work in fields unrelated to their education when their credentials are not recognized (Aydede and Dar, 2016).

6 Counterfactual Analyses

6.1 Model-based Decomposition

In this section, I decompose the immigrant-native pay gap using counterfactual analyses. Each counterfactual analysis proceeds 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 these parameters equal to the same value for all workers (typically the mean or median in the data). Then, I predict the effects on wages and employment by solving for the counterfactual equilibrium. To solve for the counterfactual equilibrium, I use an under-relaxed Jacobi iteration algorithm described in Appendix B.[34] Importantly, this approach incorporates general equilibrium responses, including any adjustments in wage markdowns, marginal products of labor, or the distribution of workers across firms.[35] 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 within-firm 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 within-firm 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 and

[34] As shown in CKMM, the model has a unique equilibrium, justifying this approach.

[35] 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 7). Instead, we must alter the model primitives that generate markdowns and examine how these changes affect markdowns and overall earnings inequality.

instead focus on the other parameters.

All of the counterfactuals are 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 2-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 2-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 $\alpha_j^{CF} = \text{median}(\{\alpha_j \mid j \in \mathcal{N} \text{ and } j \in \mathcal{C}\})$.

I. A simulated entry of new firms is created by duplicating each firm in the data. This maintains the distribution of all firm characteristics and model parameters while increasing competition.

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`): 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).

3. Policy & Market Structure (E, I): To evaluate the role of unemployment benefits (E) and competition from firm entry (I).

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).[36] 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 5, 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 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 wage-setting 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.

[36] Results available upon request.

6.2.2 Firm Productivity and Worker Sorting

The second set of experiments explores the role of firm productivity. Panel B of Table 5, 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 actually benefits immigrants relative to 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 in the true equilibrium 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 23). 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 Non-linear Interaction Effects

The final counterfactual analyses reveal that labor supply and firm productivity are not independent channels. Panel C of Table 5 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 complexity of these interactions is particularly evident in how the effect of equalizing β_k not only changes in magnitude but actually reverses sign depending on the other restrictions in the counterfactual. 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 homogenous (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).

Panel D of Table 5 introduces a final experiment on market structure through a firm entry simulation. Simply doubling the number of firms while preserving their characteristics (Counterfactual I) has a negligible effect, slightly increasing the gap to 0.166. This suggests that increasing competition, by itself, would have a minor effect on the immigrant-native pay gap. However, there is some evidence of interaction effects. When I simulate firm entry in a world where labor supply preferences are already equalized (Counterfactual A+B+I), the pay gap reverses to -0.024. Thus, when immigrants and natives have the same idiosyncratic preference parameters, increasing competition in the labor market has the opposite sign compared to the baseline scenario (the difference between counterfactual A+B+I and counterfactual A+B compared to counterfactual I) and actually reduces the immigrant-native pay gap by 3.5 percentage points.

These interaction effects demonstrate that methodologies assuming that labor supply factors and firm productivity are additively separable will likely lead to biased decompositions of the immigrant-native pay gap.

7 Conclusion

Immigrants earn 16% less than native-born workers in Canada, and this pay gap is similar in many other high-income countries. In this paper, I conduct a novel decomposition of the immigrant-native pay gap focusing on the role of labor market power and firm productivity. Using matched employer-employee data from Canada, I estimate a wage-posting model that incorporates two-sided heterogeneity and strategic interactions in wage setting. In the model, firms mark down the wage below the marginal revenue product of labor (MRPL), and the equilibrium immigrant-native pay gap arises due to differences in wage markdowns (defined as the ratio of the wage to the MRPL) and differences in the MRPL itself. The findings suggest that immigrants earn 77% of their MRPL on average, compared to 84% for natives. In addition, I decompose the immigrant-native pay gap using counterfactual analyses that take into account general equilibrium responses of workers and firms. The counterfactual analyses yield three main findings. First, differences in labor supply curves between immigrants and natives contribute significantly to the pay gap. Second, immigrants tend to work at more productive firms, driven by their tendency to work in cities where firms are more productive on average. Finally, interactions between firm productivity and labor supply are important, implying methodologies that rely on additive separability assumptions will likely produce biased decompositions of the immigrant-native pay gap.

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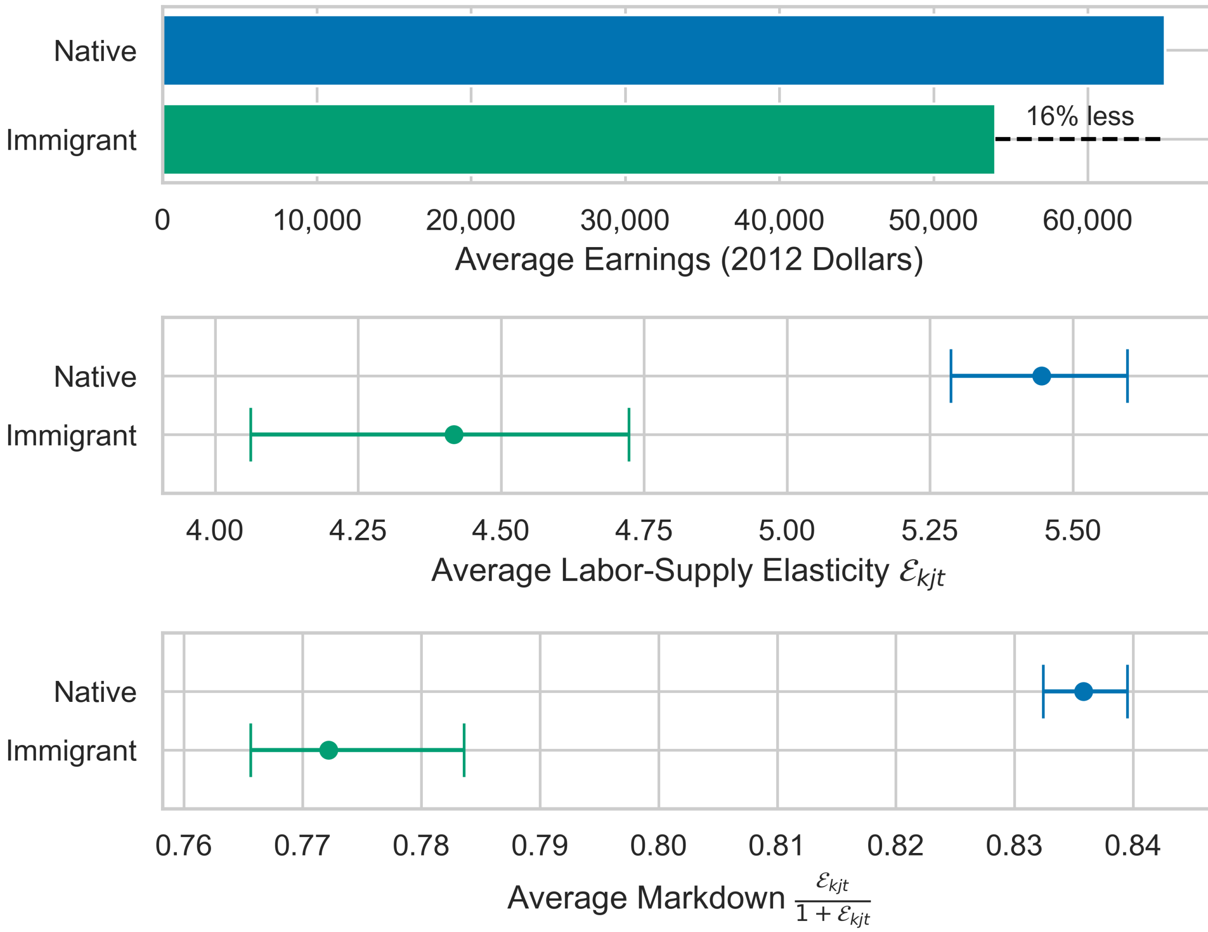
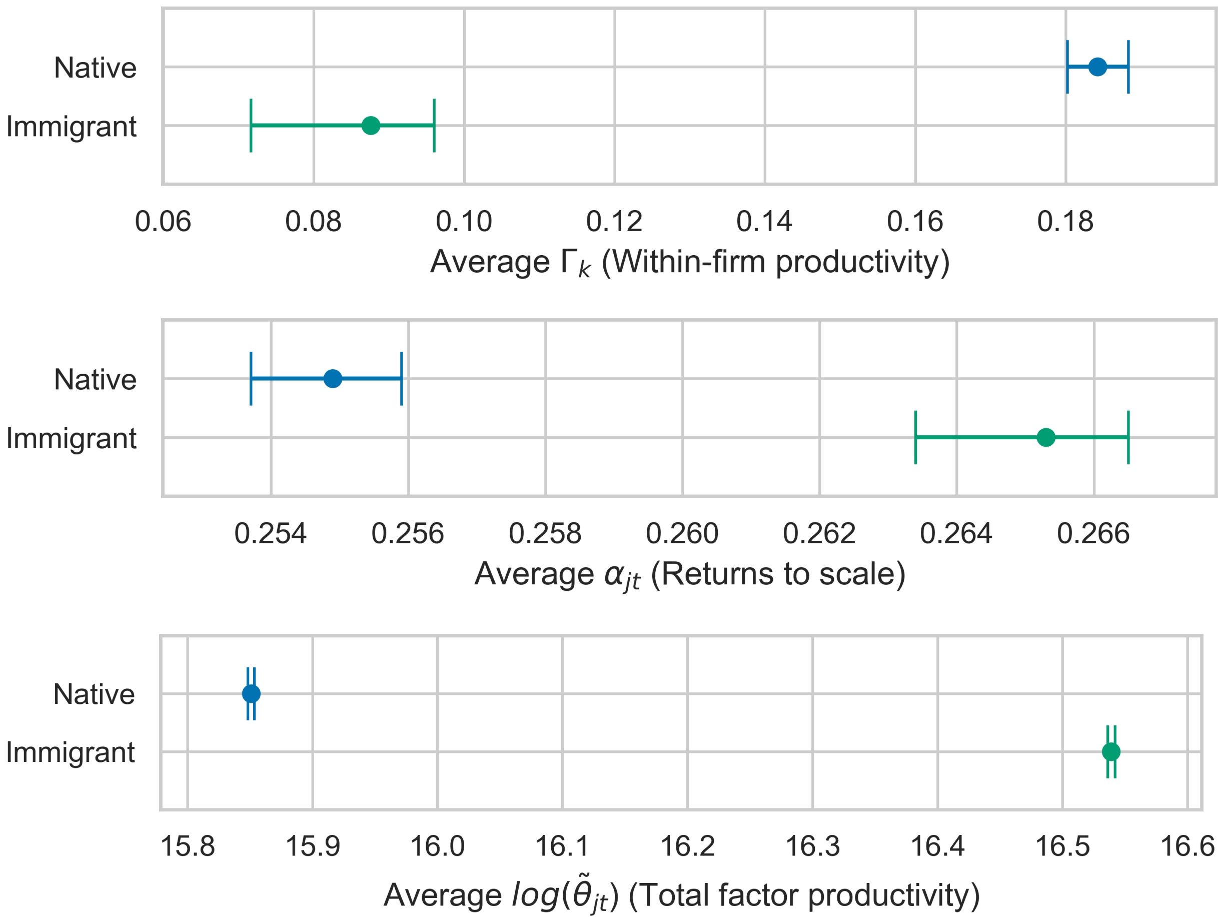
8 Figures

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



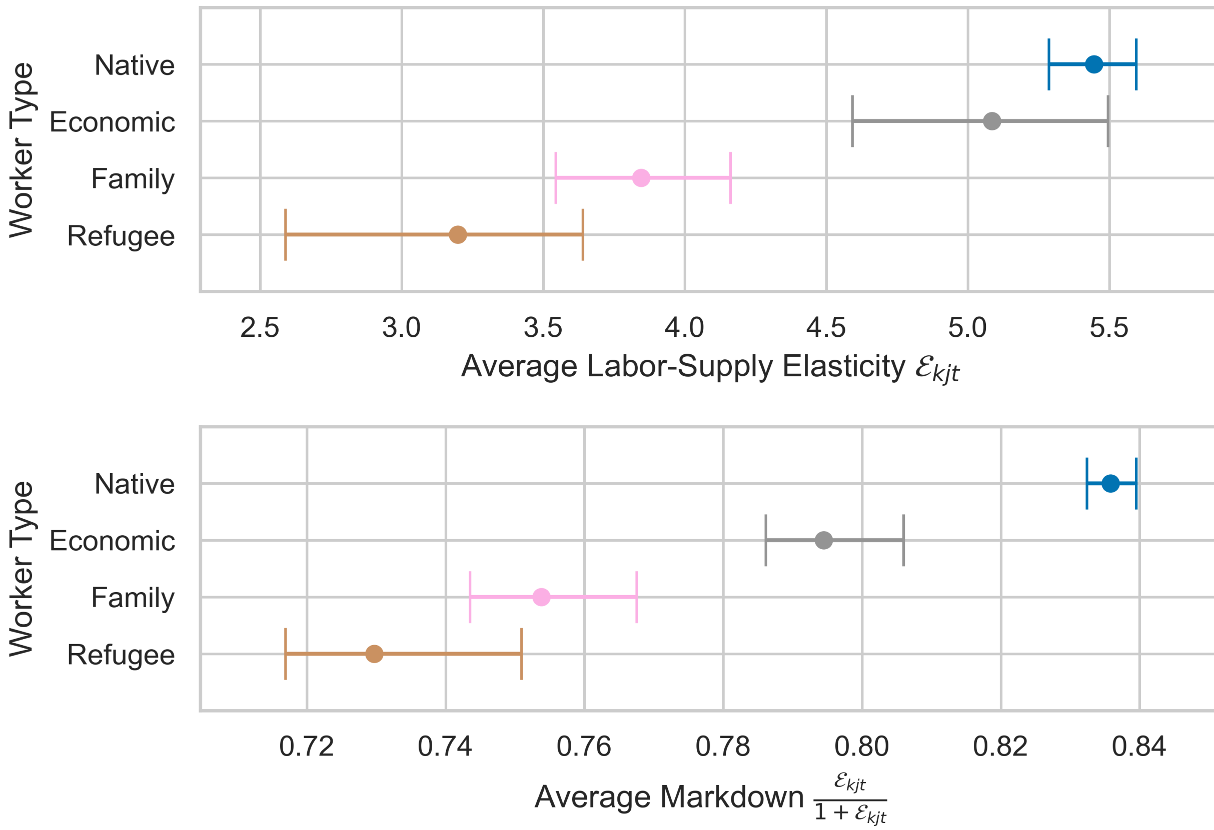
Notes: This figure presents the main estimates of labor supply elasticities and markdowns for native-born workers and immigrants. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (FOC) of the firm's profit maximization problem, the markdown is given by $\text{md}_{kjt} = \mathcal{E}_{kjt}/(1+\mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ represents the labor supply elasticity (see equation 7). Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure 2: Firm Productivity Parameters by Immigrant Status



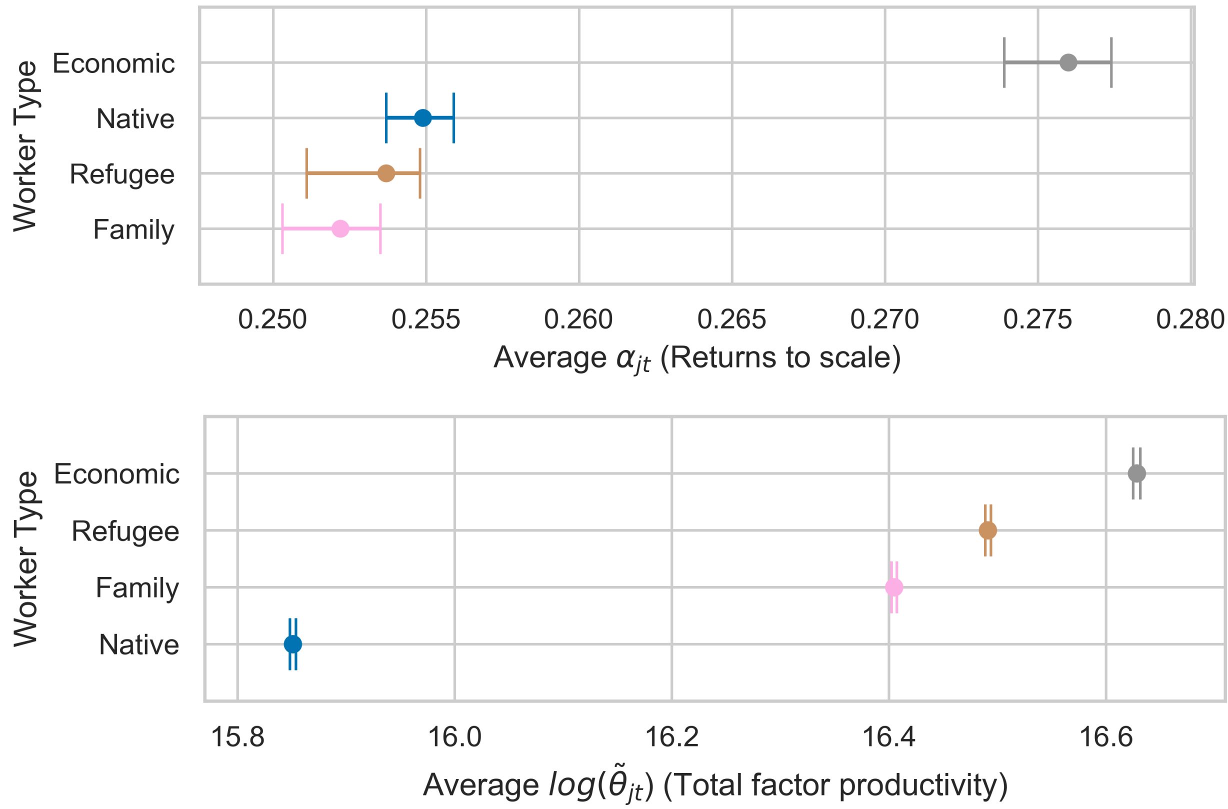
Notes: This figure presents the main estimates of the labor demand parameters. The within-firm productivity parameters γ_{kjt} are normalized within each firm so that $\sum_{k \in C_{jt}} \gamma_{kjt} = 1$, and thus, to compare the within-firm productivity parameters across firms (and construct the figure in the top panel), I first estimate equation 12 (with female natives as the omitted category). The parameter α_{jt} represents the returns to scale, and the parameter $\tilde{\theta}_{jt}$ represents total factor productivity (TFP). 95% bootstrap confidence intervals (Hall, 1992) are reported. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure 3: Labor-Supply Elasticities and Wage Markdowns by Immigration Category



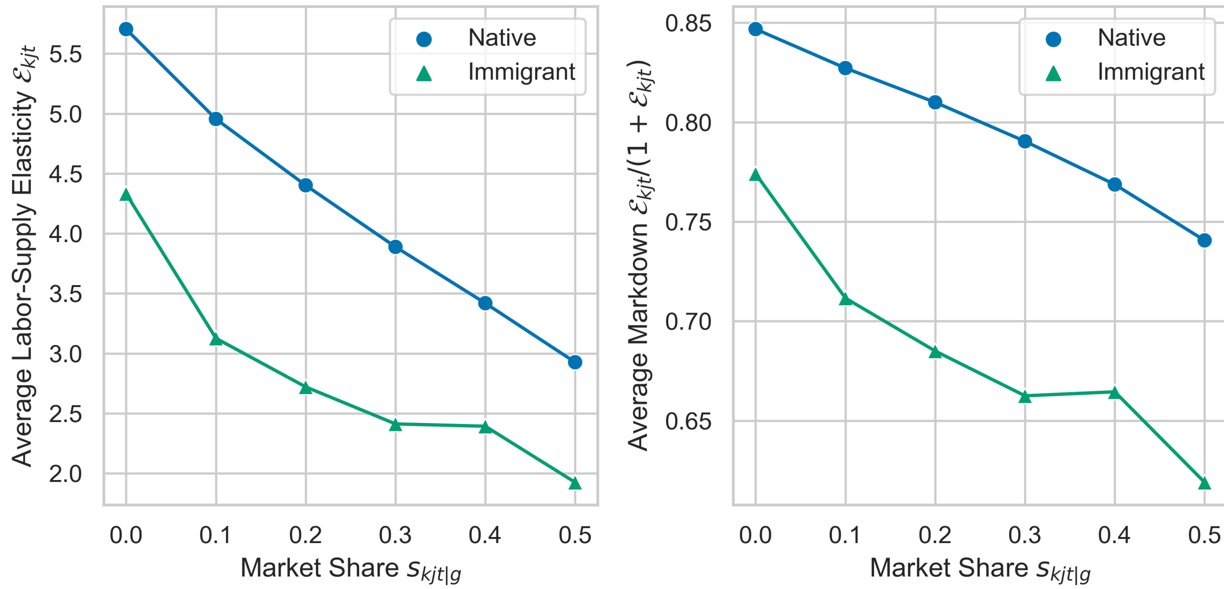
Notes: This figure presents the main estimates of labor supply elasticities and markdowns for native-born workers and three categories of immigrant workers: economic class, family class, and refugees. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (FOC) of the firm's profit maximization problem, the markdown is given by $\mathrm{md}_{kjt} = \mathcal{E}_{kjt}/(1 + \mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ represents the labor supply elasticity (see equation 7). Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure 4: Between-firm Productivity by Immigration Category



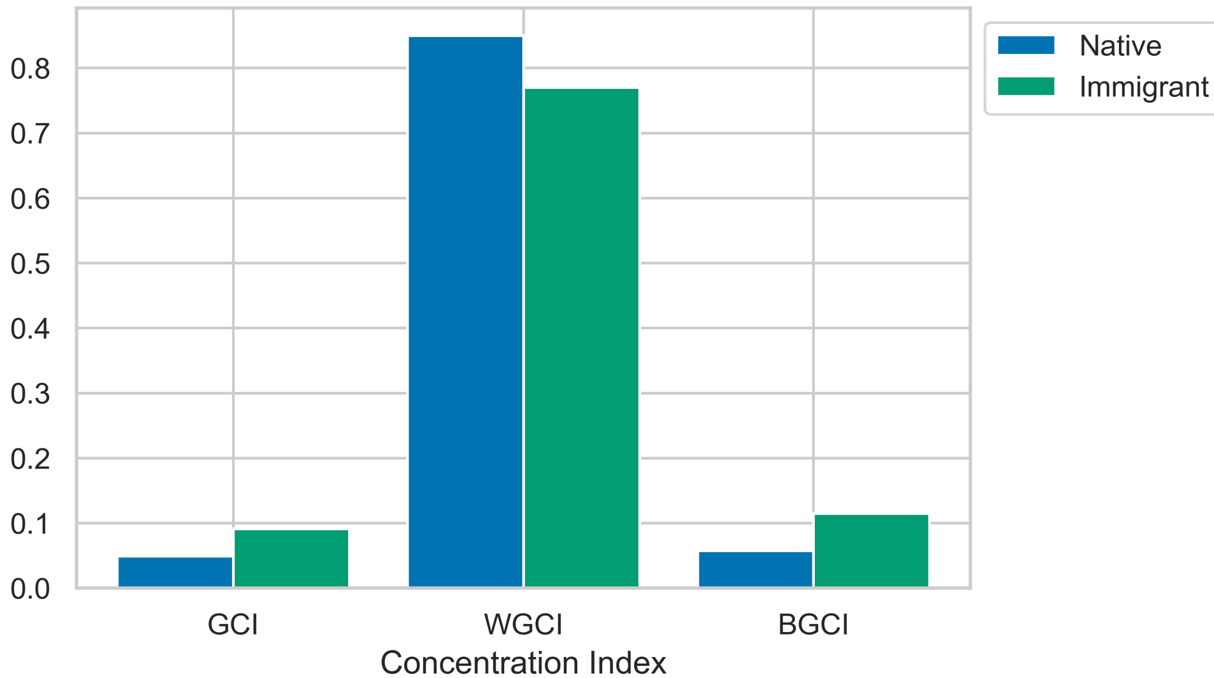
Notes: This figure presents the main estimates of the between-firm labor demand parameters for native-born workers and three categories of immigrant workers: economic class, family class, and refugees. The parameter α_{jt} captures returns to scale, and the parameter $\tilde{\theta}_{jt}$ captures total factor productivity (TFP). "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variable (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

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



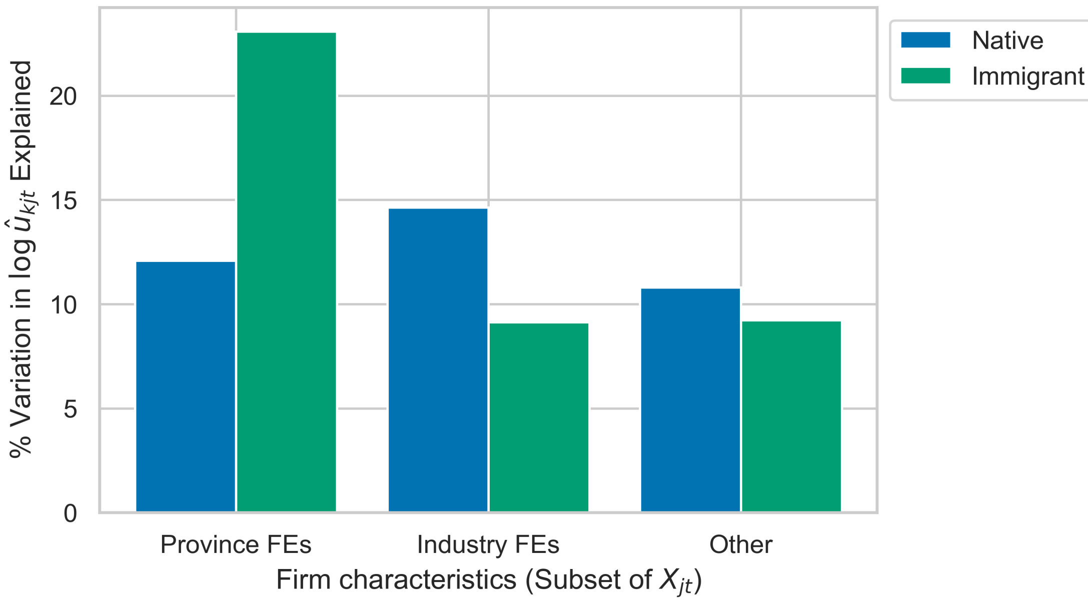
Notes: This figure illustrates the relationship between labor supply elasticity, wage markdown, and firm size (market share), separately for immigrants and natives. Market share, $s_{kjt|g}$, is defined as the share of type-k workers in market g employed by firm j at time t: $s_{kjt|g} \equiv l_{kjt}/\left(\sum_{j\in\mathcal{J}_g} l_{kjt}\right)$, where l_{kjt} represents the employment of type-k workers at firm j at time t, and $\mathcal{J}_g$ is the set of firms in market g. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (FOC) of the firm's profit maximization problem, the markdown is given by $\text{md}_{kjt} = \mathcal{E}_{kjt}/(1+\mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ represents the labor supply elasticity (see equation 7). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (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 Canadian Employer-Employee Dynamics Database (CEEDD).

Figure 7: Variation in Estimated Amenities $\log \widehat{u_{kjt}}$ Explained By Firm Characteristics



Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with deterministic preferences for amenities. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate equation 14 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 time-varying covariates) 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 $\Delta R^2 \equiv R^2_{full} - R^2_{partial}$. Standard errors are clustered at the local labor market (CMA $\times$ industry) level.

9 Tables

Table 1: Summary Statistics

	Natives (1)	All Immigrants (2)	Economic Class (3)	Family Class (4)	Refugees (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	65,000	54,000	60,000	48,000	47,000
Mean earnings (both imms and natives at firm)	72,000	56,000	62,000	49,000	48,000
Mean earnings (only imms or only natives at firm)	55,000	42,000	45,000	39,000	38,000
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 with immigrant and native coworkers	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
Mean log revenue	16.5	17.2	17.4	17.1	17.0
Median firm size	29	75	85	63	72
Number of person-year obs	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 firms	900,000	450,000	320,000	260,000	150,000

This table contains summary statistics for the sample used in the estimation of the model. All monetary units are in \$2012 dollars. Numbers in the table are rounded to comply with Statistics Canada's vetting rules for intermediate output. Data cleaning procedures follow Dostie et al. (2023) and Li et al. (2023) closely. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table 2: 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 2.4). 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 2.2). Both Instrumental variables (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 3: Overview of Labor-supply Elasticity and Markdown Estimates

Panel A: Estimated Values in the Full Sample					
		IV	95% CI	OLS	95% CI
Labor-supply Elasticity	$\mathcal{E}_{kjt}$	5.25	[5.16; 5.46]	0.29	[0.29; 0.29]
Markdown ($\text{md}_{kjt} = \frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}$)	md_{kjt}	0.82	[0.82; 0.83]	0.22	[0.21; 0.22]
Panel B: Estimated Values for Natives Only					
		IV	95% CI	OLS	95% CI
Labor-supply Elasticity	$\mathcal{E}_{kjt}$	5.45	[5.31; 5.65]	0.34	[0.34; 0.34]
Markdown ($\text{md}_{kjt} = \frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}$)	md_{kjt}	0.84	[0.83; 0.84]	0.25	[0.25; 0.26]
Panel C: Estimated Values for Immigrants Only					
		IV	95% CI	OLS	95% CI
Labor-supply Elasticity	$\mathcal{E}_{kjt}$	4.42	[4.19; 4.75]	0.07	[0.07; 0.07]
Markdown ($\text{md}_{kjt} = \frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}$)	md_{kjt}	0.77	[0.77; 0.78]	0.05	[0.05; 0.06]

This table presents the main estimates of labor-supply elasticities and markdowns. The "average" of any parameter is defined as the employment-weighted average in the data (see Section 2.4). Panel A reports average estimates for the entire sample. Panel B reports average estimates for native-born workers only. Panel C reports average estimates for immigrants only. Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (FOC) of the firm's profit maximization problem, the markdown is given by $\text{md}_{kjt} = \mathcal{E}_{kjt}/(1 + \mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ is the labor-supply elasticity (see equation 7). IV and OLS estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table 4: Overview of Labor Demand Parameter Estimates

Panel A: Estimated Values in the Full Sample					
		IV	95% CI	OLS	95% CI
Within-firm productivity	γ_{kjt}	0.34	[0.34; 0.34]	0.31	[-0.46; 0.44]
Total factor productivity	$\log(\tilde{\theta}_{jt})$	15.99	[15.98; 15.99]	-	[-; -]
Returns to scale	α_{jt}	0.26	[0.26; 0.26]	34.99	[67.7; 73.1]
Panel B: Estimated Values for Natives Only					
		IV	95% CI	OLS	95% CI
Within-firm productivity	γ_{kjt}	0.38	[0.38; 0.38]	0.3	[-0.34; 0.44]
Total factor productivity	$\log(\tilde{\theta}_{jt})$	15.85	[15.85; 15.85]	-	[-; -]
Returns to scale	α_{jt}	0.25	[0.25; 0.26]	20.89	[40.19; 43.56]
Panel C: Estimated Values for Immigrants Only					
		IV	95% CI	OLS	95% CI
Within-firm productivity	γ_{kjt}	0.18	[0.18; 0.18]	0.35	[-0.58; 1.01]
Total factor productivity	$\log(\tilde{\theta}_{jt})$	16.54	[16.54; 16.54]	-	[-; -]
Returns to scale	α_{jt}	0.27	[0.26; 0.27]	94.63	[184.15; 197.73]

This table presents the main estimates of the labor demand parameters. The "average" of any parameter is defined as the employment-weighted average in the data (see Section 2.4). 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 labor demand parameters are defined in the production function (see equation 6). The parameter γ_{kjt} measures worker skill and captures within-firm productivity. The parameter $\tilde{\theta}_{jt}$ represents total factor productivity (TFP). The parameter α_{jt} captures the returns to scale of the production function. Both IV and OLS estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table 5: Counterfactual Analyses

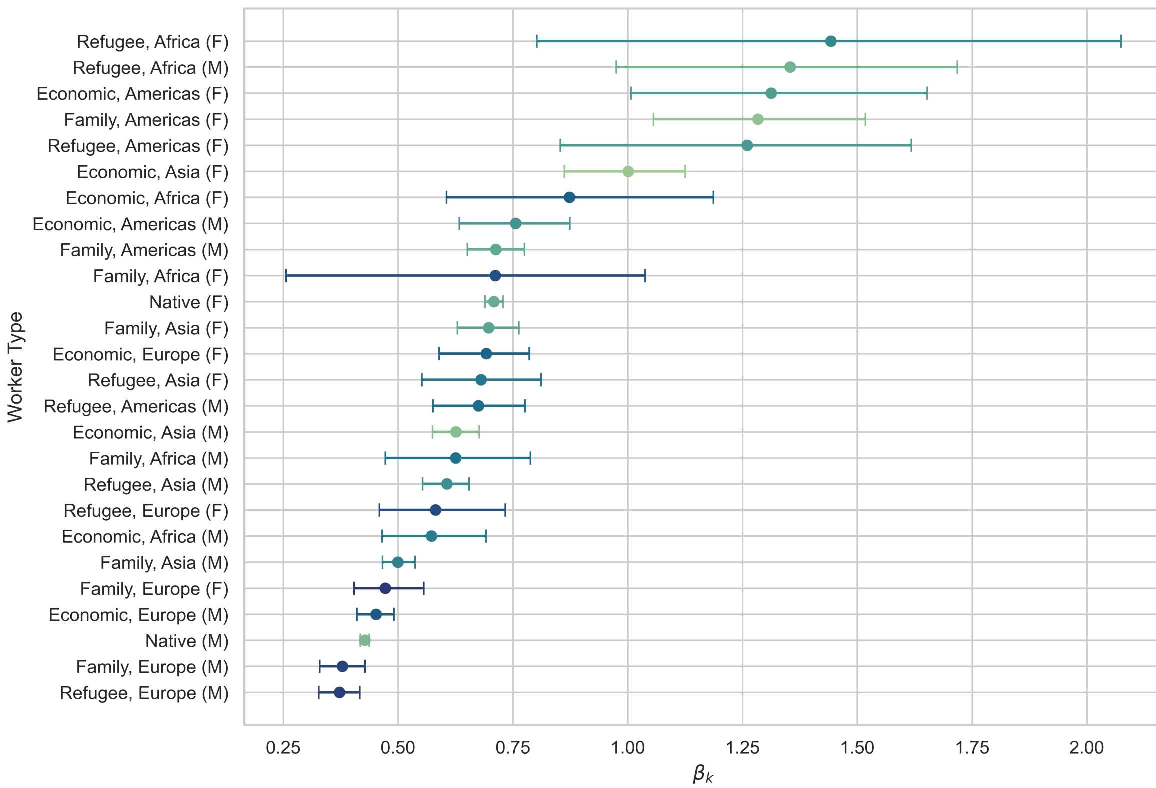
Counterfactual	Description	Pay Gap
Panel A: Labor Supply Counterfactuals		
A	Avg. β_k	0.107
B	Avg. σ_{kg}	0.075
A+B	Avg. β_k, σ_{kg}	0.011
Panel B: Firm Productivity Counterfactuals		
C	Median $\tilde{\theta}_j$	0.442
D	Median α_j	0.217
C+D	Median $\tilde{\theta}_j, \alpha_j$	0.292
F	CMA median $\tilde{\theta}_j, \alpha_j$	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
Panel D: Firm Entry		
I	Firm Entry Simulation	0.166
A+B+I	Avg. β_k, σ_{kg} + Entry	-0.024
C+D+I	Median $\tilde{\theta}_j, \alpha_j$ + Entry	0.299

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. Panel D presents counterfactuals where there is an increase in the number of firms in each market. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Appendices

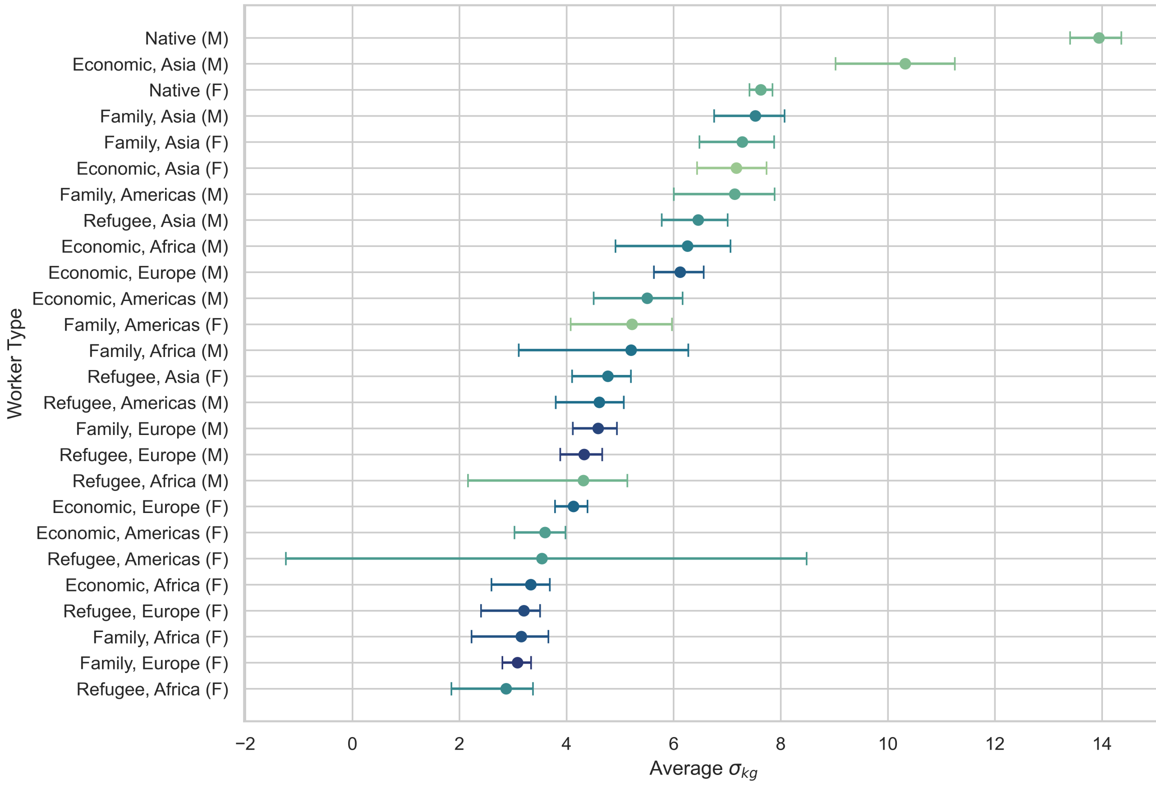
A Appendix Figures and Tables

Figure A1: Estimates of β_k by k-group



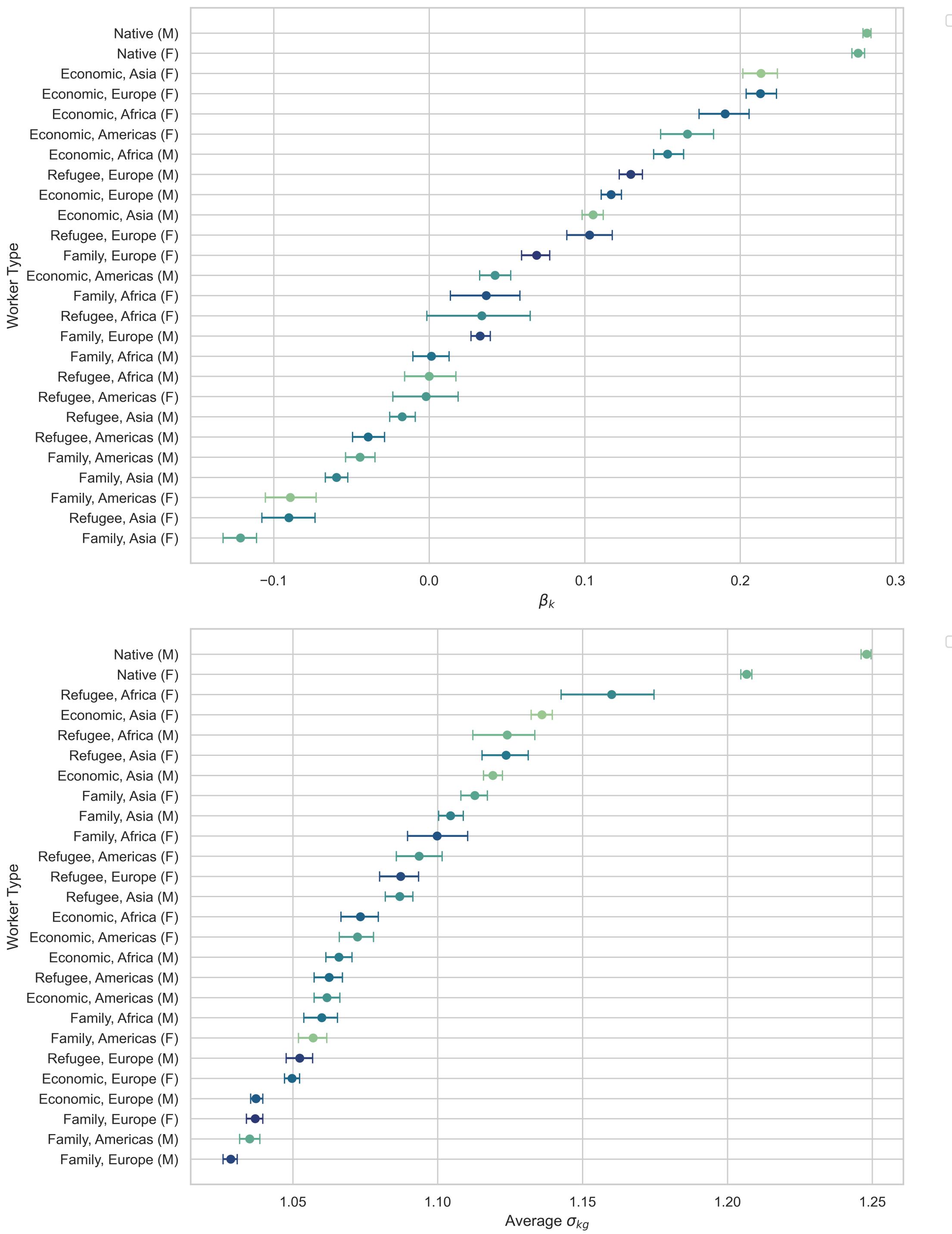
Notes: This figure shows the estimates of β_k. The parameter β_k is the marginal utility of the wage in the utility function (see equation 1). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

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



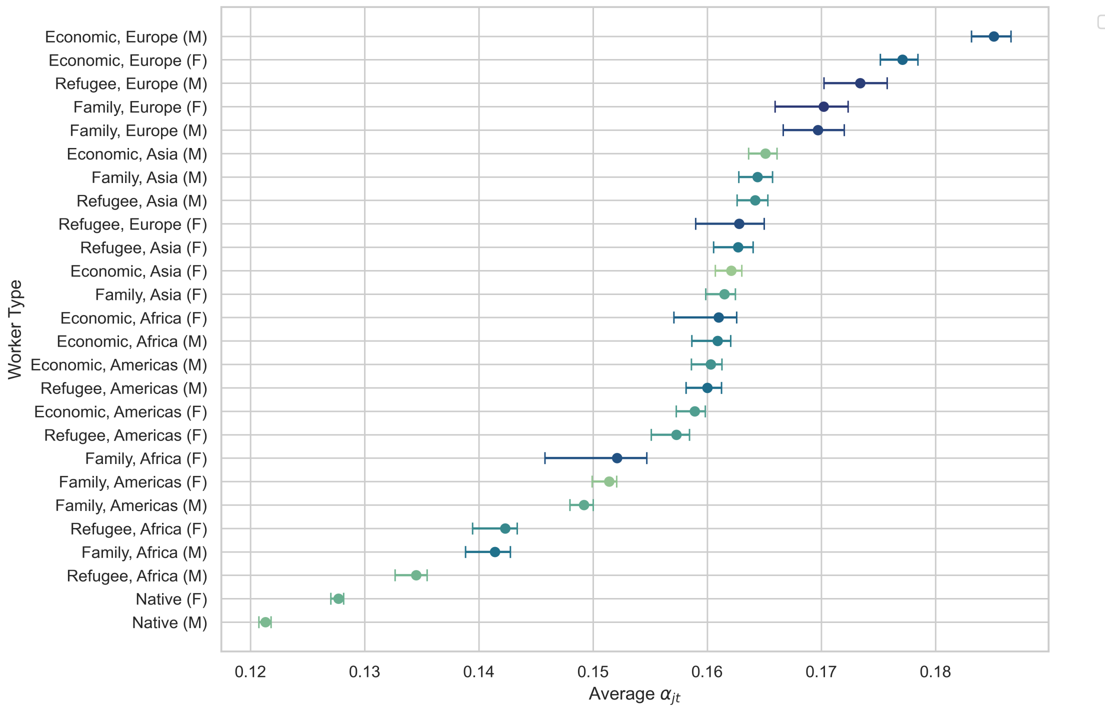
Notes: This table shows the estimates of the average σ_{kg} for each k-group. The parameter σ_{kg} is the "nest parameter" that is related to the correlation of the idiosyncratic preferences (see section 2.2). "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A3: OLS estimates of labor-supply primitives by k-group



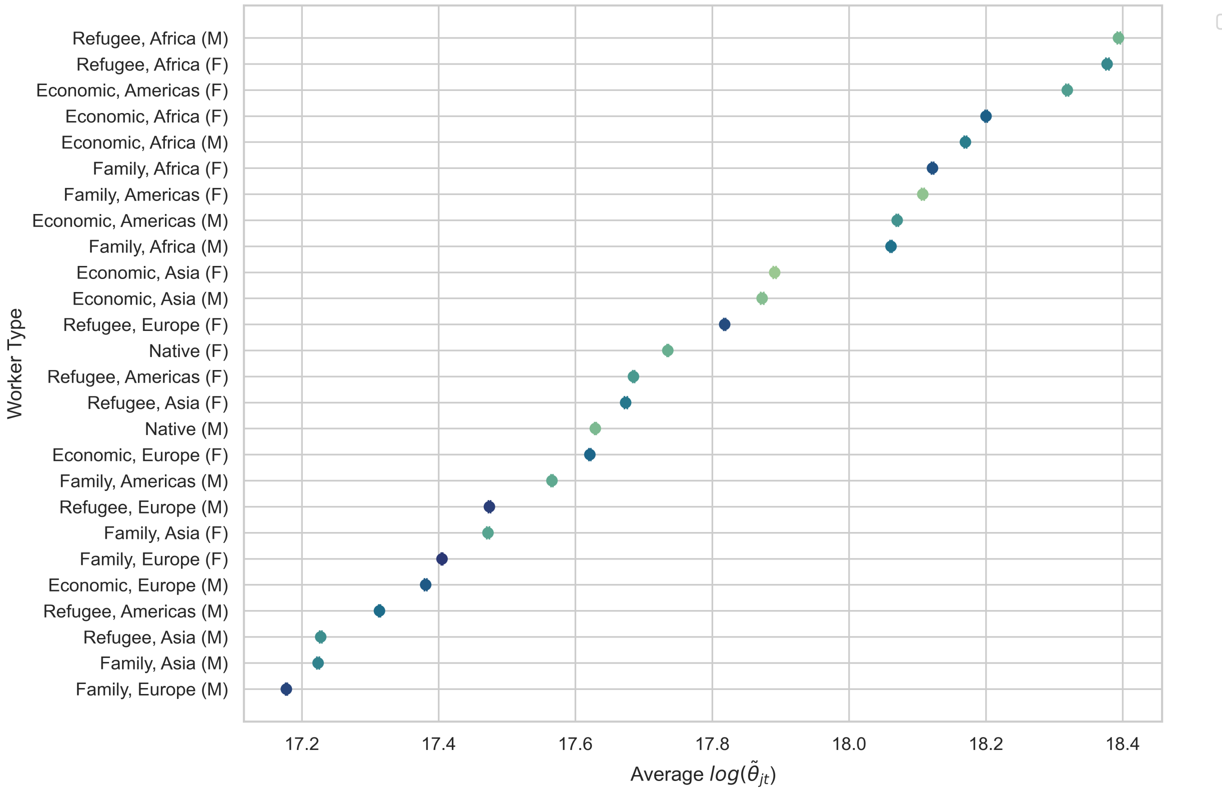
Notes: This figure presents the OLS estimates of the labor-supply parameters β_k and σ_{kg}. 95% bootstrap confidence intervals are reported (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A4: Estimates of average returns to scale by k-group



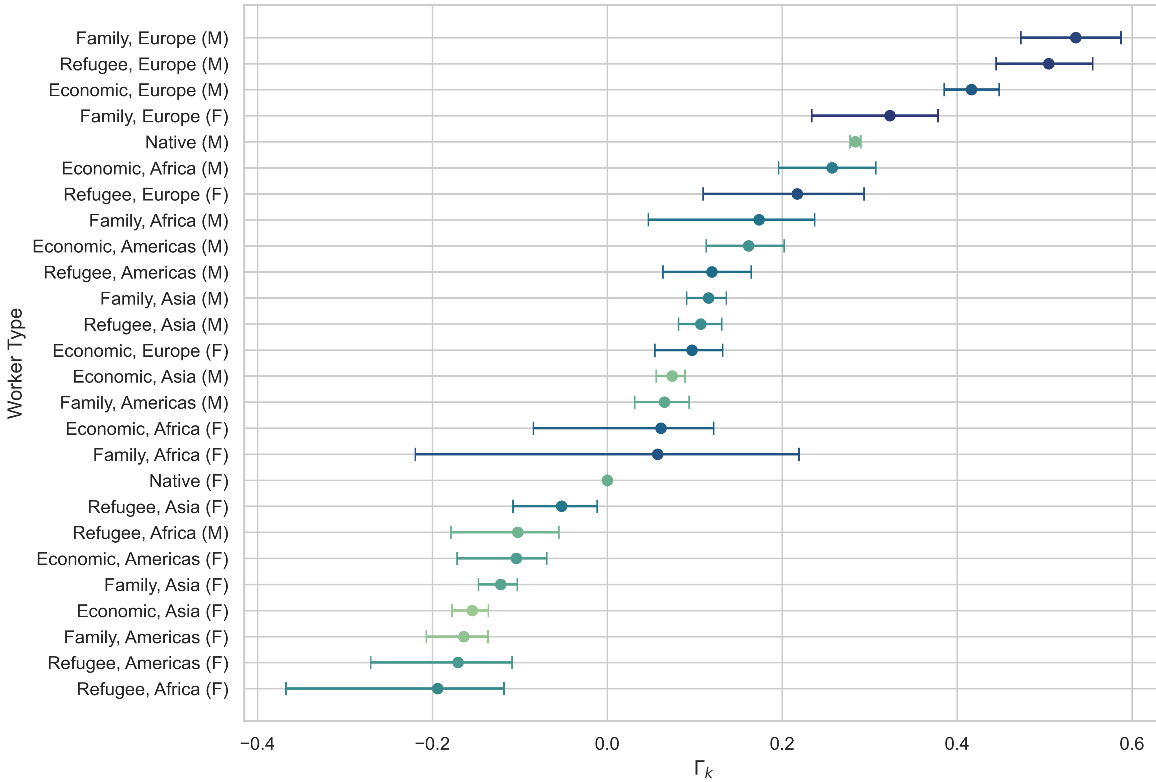
Notes: This figure shows the estimates of the average α_{jt} for each k-group. The parameter α_{jt} captures the returns to scale in the production function (see equation 6). "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A5: Estimates of average TFP by k-group



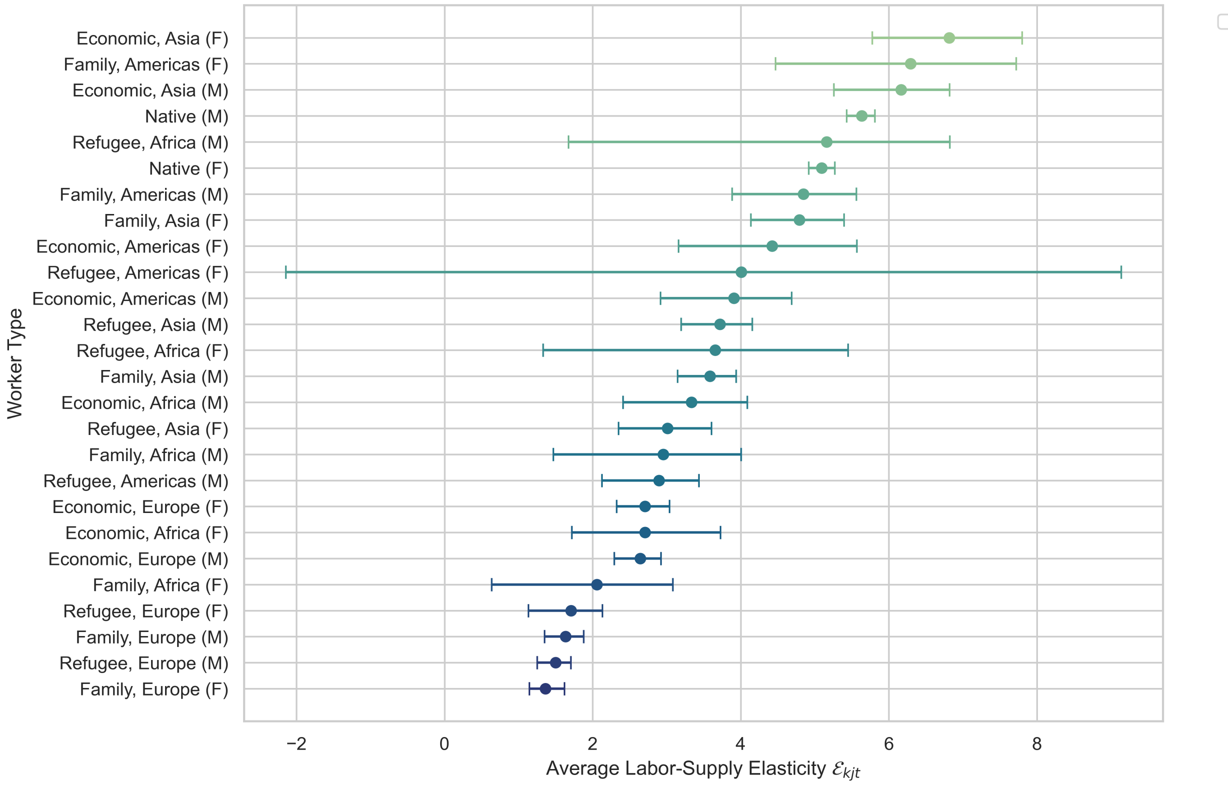
Notes: This figure shows the estimates of the average $\log(\tilde{\theta}_{jt})$ for each k-group. The parameter $\log(\tilde{\theta}_{jt})$ is the parameter that captures total factor productivity (TFP) in the production function (see equation 6). "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A6: Heterogeneity in Worker Skill by k-Group



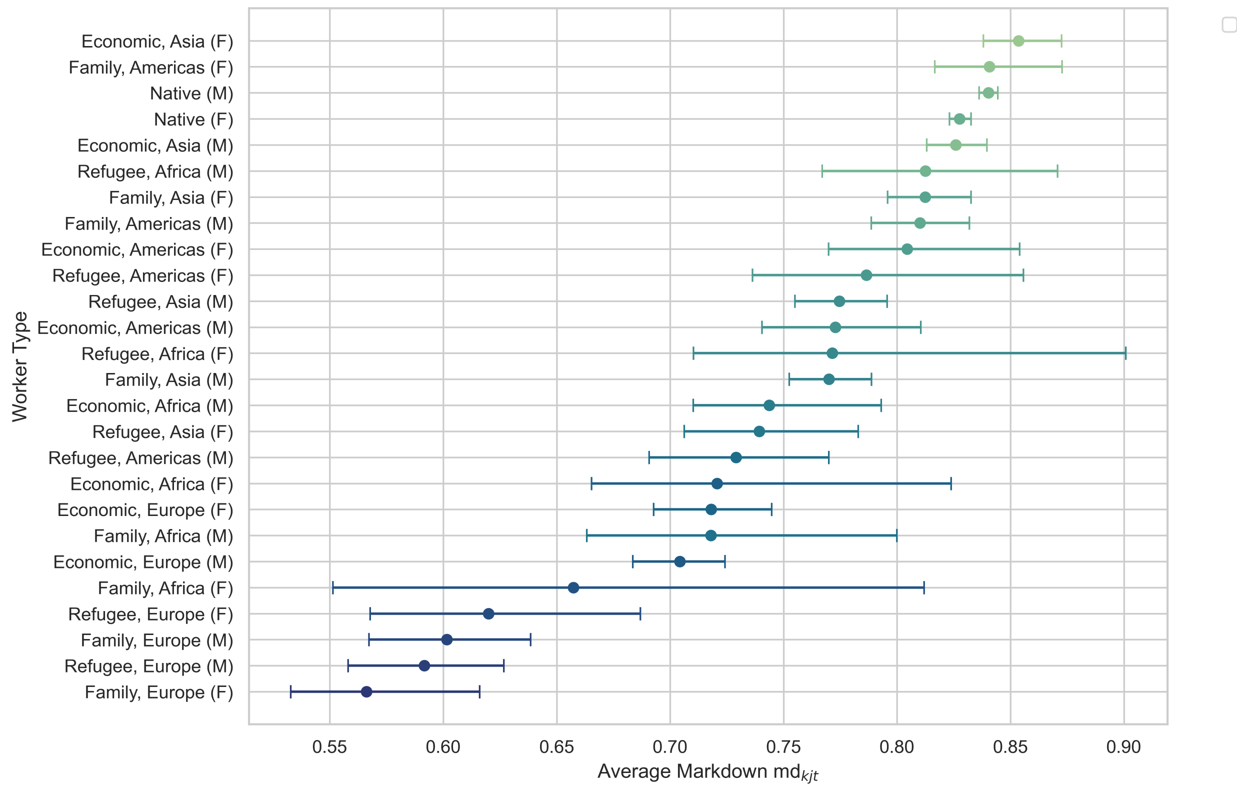
Notes: This figure presents the main estimates of worker skill (Γ_k) for each k-group, obtained from the estimation of equation 12. Ordinary Least Squares (OLS) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A7: Heterogeneity in Labor-Supply Elasticities by k-Group



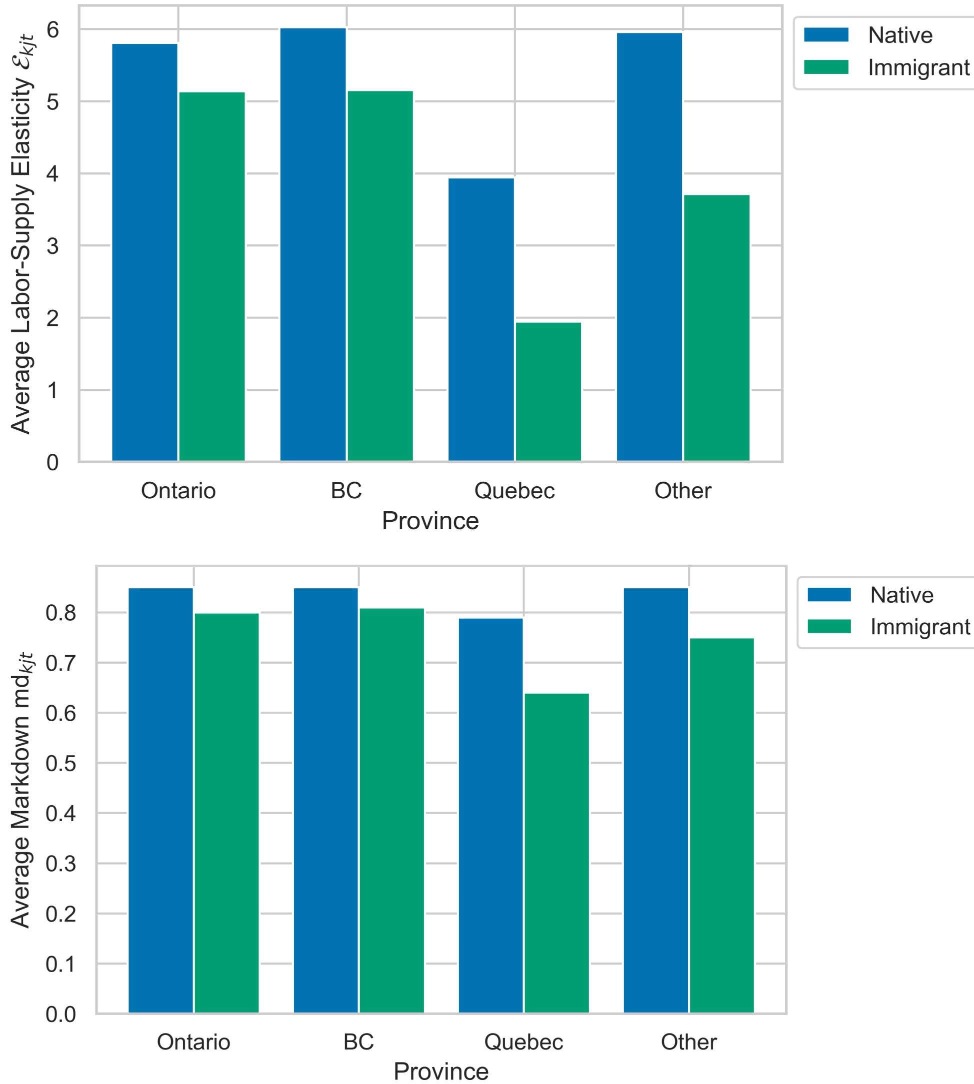
Notes: This figure presents the main estimates of labor-supply elasticities for each k-group. "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A8: Heterogeneity in Wage Markdowns by k-Group



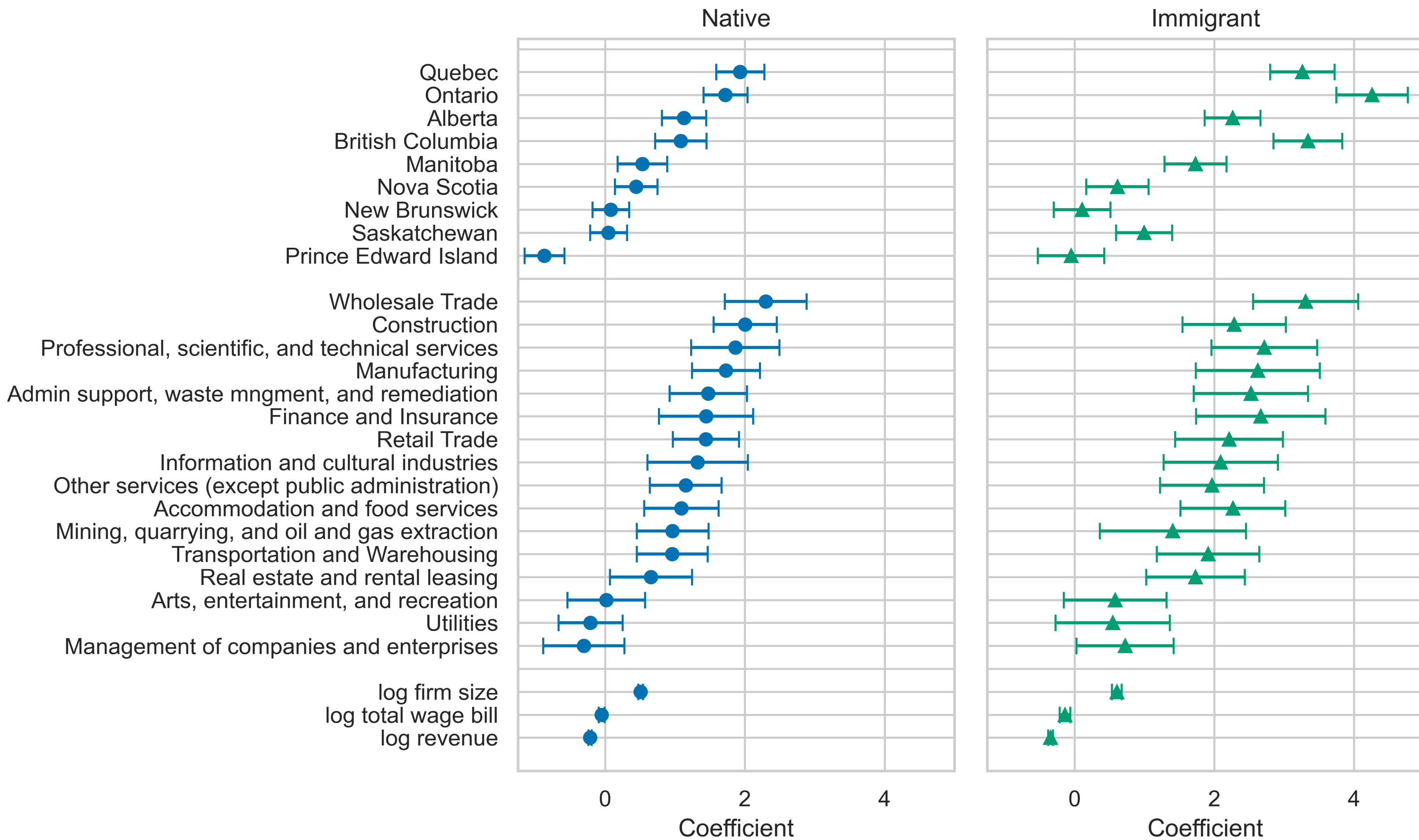
Notes: This figure presents the main estimates of wage markdowns for each k-group. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (FOC) of the firm's profit maximization problem, the markdown is given by $\text{md}_{kjt} = \mathcal{E}_{kjt}/(1 + \mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ represents the labor supply elasticity (see equation 7). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A9: Heterogeneity in Labor-Supply Elasticities and Wage Markdowns by Province



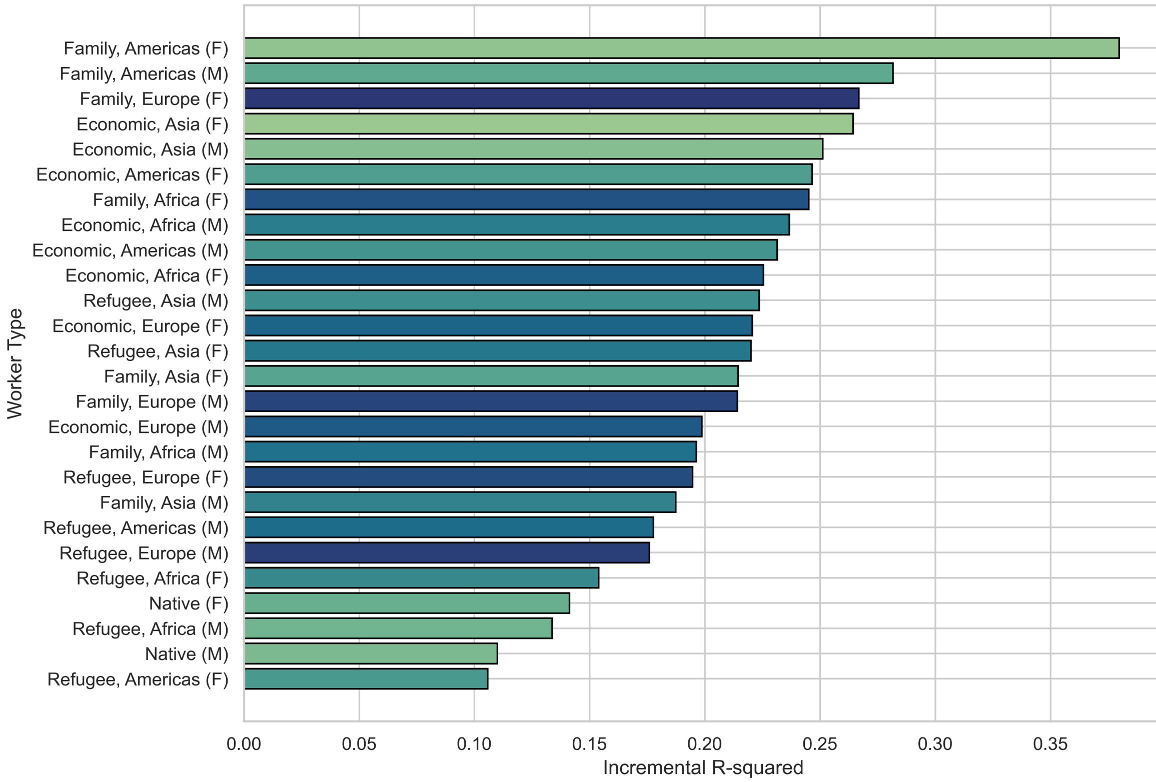
Notes: This figure presents the main estimates of labor supply elasticities and markdowns across provinces. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (FOC) of the firm's profit maximization problem, the markdown is given by $\mathrm{md}_{kjt} = \mathcal{E}_{kjt}/(1 + \mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ represents the labor supply elasticity (see equation 7). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A10: Observed Characteristics Correlated with Deterministic Preferences for Amenities



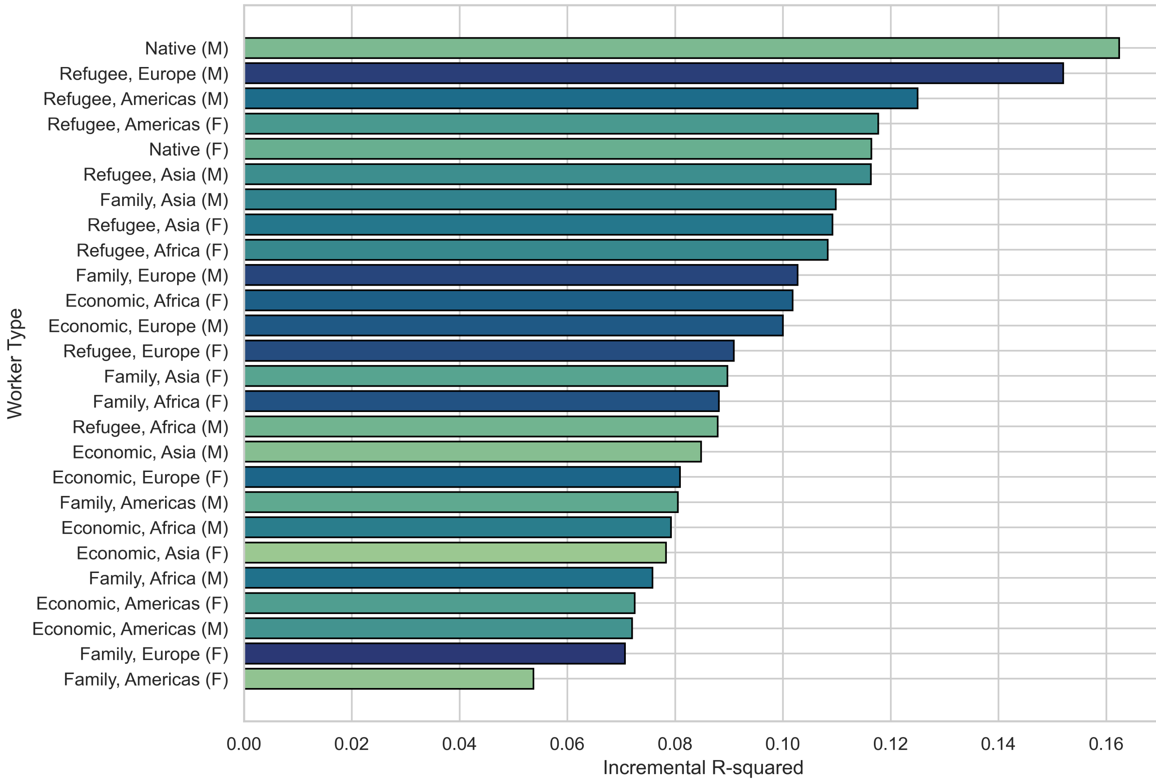
Notes: This figure presents the results from the estimation of equation 14. Standard errors are clustered at the local labor market (CMA $\times$ industry) level. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A11: Incremental R-squared Analyses (Provinces)



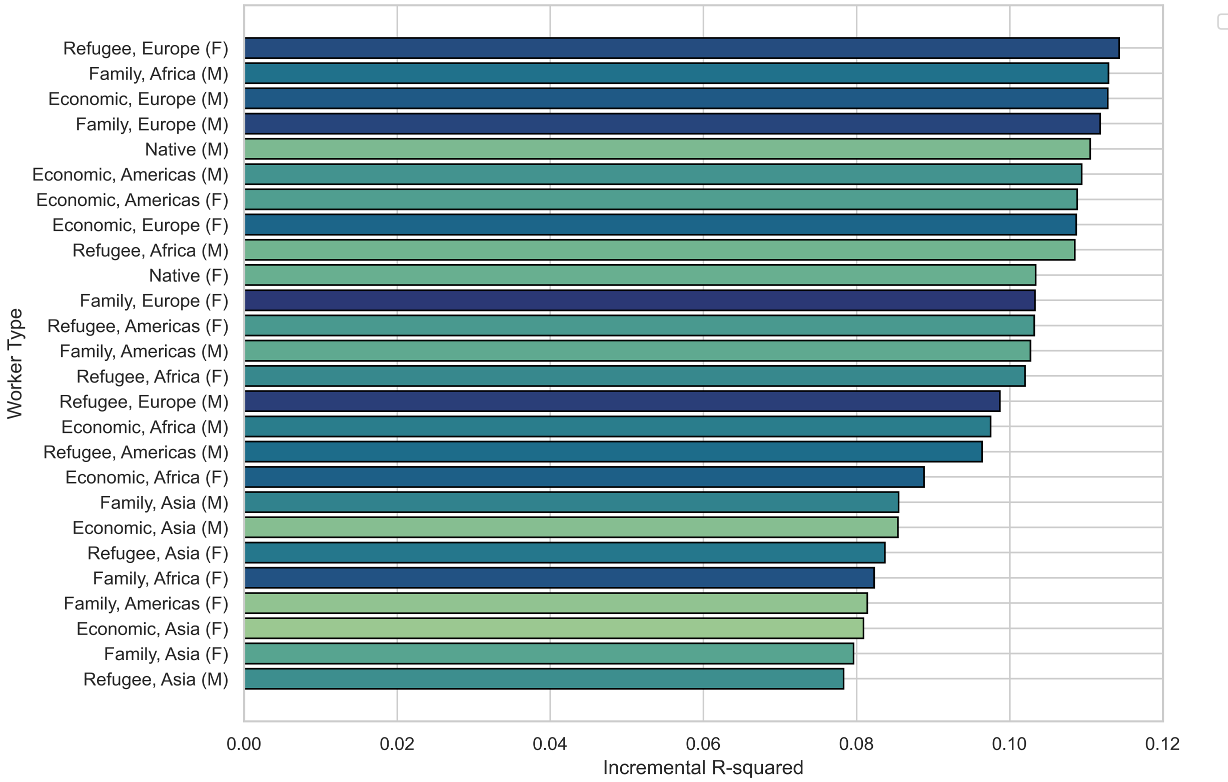
Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with deterministic preferences for amenities. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate equation 14 with all covariates included on the right-hand side and record the R-squared of the full model, denoted as R^2_{full}. Next, I remove province fixed effects and re-estimate the equation. The new R-squared, after excluding this group of covariates, is denoted as R^2_{-prov}. The incremental R-squared is then calculated as $\Delta R^2_{prov} \equiv R^2_{full} - R^2_{-prov}$. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A12: Incremental R-squared Analyses (Industries)



Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with deterministic preferences for amenities. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate equation 14 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 industry fixed effects and re-estimate the equation. The new R-squared, after excluding this group of covariates, is denoted as R^2_{-ind}. The incremental R-squared is then calculated as $\Delta R^2_{ind} \equiv R^2_{full} - R^2_{-ind}$. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A13: Incremental R-squared Analysis (time-varying firm characteristics)



Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with deterministic preferences for amenities. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate equation 14 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 time-varying firm characteristics (revenue, size, and total wage bill) and re-estimate the equation. The new R-squared, after excluding this group of covariates, is denoted as R^2_{-tv}. The incremental R-squared is then calculated as $\Delta R^2_{tv} \equiv R^2_{full} - R^2_{-tv}$. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table A1: F-statistics from the first stage of estimating equation 4

$k-$ 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 8. Note that when estimating the model, the σ_{kg} parameter is assumed to be the same for all nests g that are located within the same province group (Ontario, Quebec, British Columbia, all other provinces) conditional on worker type k; see footnote 23. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Table A2: 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 15. 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 14). 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 15. 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.

Table A3: Correlations of worker skill with observable characteristics

Dependent variable: Γ_{kt}	(1)
log(avg years of schooling)	1.241
	(0.258)
log(avg years of experience)	0.845
	(0.291)
log(share speaks english or french)	-0.085
	(0.148)
Observations	432
R-squared	0.314

This table presents results from the estimation of equation **??**. The dependent variable "Γ_{kt} refers to the worker-type by year fixed effects obtained from the estimation of equation 12. The right-hand side variables are averages of productivity-related variables (education, experience, and language ability) for each worker type k in year t. Standard errors are clustered at the k-type level. *Source:* Author's calculations from the Canadian Employer-Employee Dynamics Database (CEEDD)

Table A4: Incremental R-squared Analyses (Worker Skill)

Incremental R-squared Results	
ΔR^2: log(avg years of schooling)	0.279
ΔR^2: log(avg years of experience)	0.154
ΔR^2: log(share speaks english or french)	0.011

This table presents the results from the incremental R-squared analyses that examine the relationship between model estimates of worker skill and observed measures of education, experience, and language ability. The results are obtained using the following procedure. First, I estimate equation 17 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 covariate and re-estimate the equation. The new R-squared, after excluding the covariate, is denoted as R^2_{excl}. The incremental R-squared is then calculated as $\Delta R^2 \equiv R^2_{full} - R^2_{excl}$. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

B 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 $t = 2002, ..., 2019$.

C Sources of productivity differences

To investigate factors correlated with productivity, I first estimate within-firm productivity for each k-type in each year t by running the following regression:

$$\log(\hat{\gamma}_{kjt}) = \Gamma_{kt} + \psi_{jt} + e^{\gamma}_{kjt}, \tag{16}$$

where $\hat{\gamma}_{kjt}$ is the estimated within-firm productivity (see Section 5.1), Γ_{kt} represents worker-type-by-year fixed effects, ψ_{jt} represents firm-by-year fixed effects, and e^{γ}_{kjt} is the error term. With the estimated worker-type-by-year fixed effects, $\hat{\Gamma}_{kt}$, I then estimate the following regression:

$$\hat{\Gamma}_{kt} = \beta^{\gamma}_0 + X'_{kt}\beta^{\gamma}_1 + \nu^{\gamma}_{kt}, \tag{17}$$

where X_{kt} denotes characteristics of type-k workers in year-t that are related to productivity (log average years of schooling, log average years of experience, and the log of the share of workers who speak English or French), β^{γ}_1 is a vector of coefficients, and ν^{γ}_{kt} is the error term. Since I only observe education and language ability for immigrants in the data, I estimate equation 17 using data on the 24 immigrant types and exclude native-born types.

The results are presented in Table A3. The estimates indicate that k-types with higher within-firm productivity tend to have higher levels of education and experience, and these associations are statistically significant. Specifically, a 1% increase in average years of schooling is associated with a 1.24% increase in within-firm productivity, while a 1% increase in average experience is associated with a 0.85% increase in within-firm productivity. These findings are intuitive: workers with more education or experience tend to be more productive. However, there is no statistically significant relationship between within-firm productivity and language ability.

Additionally, I conduct incremental R-squared analyses to assess the extent to which observable characteristics explain variation in within-firm productivity. The results are shown in Table A4. Education accounts for approximately 28 percent of the variation in within-firm productivity, while experience explains around 15 percent.