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 the wage below the marginal revenue product of labor (MRPL), and the equilibrium immigrant-native pay gap arises due to differences in wage markdowns and MRPL. The findings suggest that immigrants earn 77% of their MRPL on average, compared to 84% for natives. In addition, immigrants tend to work at more productive firms compared to natives, although they are less productive on average relative to natives within the same firm. To decompose the pay gap into labor supply and demand factors, I conduct counterfactual analyses that take into account general equilibrium effects. The results suggest that within-firm productivity increases the gap, while between-firm productivity decreases it. Differences in between-firm productivity are driven by immigrants sorting into cities with more productive firms, although they tend to work at less productive firms compared to natives within the same city. When all productivity heterogeneity is eliminated, the gap widens, suggesting that differences in labor supply contribute significantly to the immigrant-native pay gap.

Keywords: Immigration, inequality, monopsony, compensating differentials, 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 earnings into individual-level and firm-level components find that firm-specific pay premiums contribute significantly to the immigrant-native pay gap (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. 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 framework in Chan et al. (2024), I estimate a wage-posting model that incorporates two-sided

[1] Due to recent record-breaking growth in immigration, roughly one-quarter of individuals in Canada are immigrants (StatsCan, 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 markdown 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, in Card et al. (2018), 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).

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, immigrants tend to work at more productive firms relative to natives, although they are less productive on average relative to natives within the same firm. To decompose the immigrant-native pay gap into labor supply and demand factors, I conduct counterfactual analyses that take into account general equilibrium effects. When all firm productivity heterogeneity is eliminated, the gap widens to 24%, highlighting the significant contribution of differences in labor supply to 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 specification for employer 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 equilbrium 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 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 employment share for a worker type and a firm relative to the share of non-employment for that worker type as a function of the wages and market share. Here, the "employment share" refers to the firm's share of employment for the worker type among all workers in the economy, whereas the "market share" (sometimes called the "inside share") is the firm's share of employment for the worker type within the local labor market. The error term in the quasi-supply function

for strategic interactions in wage setting. The remaining identification problem is that deterministic preferences for amenities may be correlated with the wage or 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 productivity are persistent, while innovations in deterministic preferences for amenities are transitory.[6] 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.[7]

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.[8] 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.[9]

In Section 5, I discuss the main estimates of the model parameters. There are three main findings. The first key finding is that labor power contributes significantly to earnings inequality between immigrants and natives. 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. The average labor supply elasticity in Canada is 5.25, consistent with findings from other countries where elasticities typically

is the deterministic preferences for amenities.

[6]Importantly, these identification assumptions do not restrict correlations between the average levels of the deterministic preferences and wages or market shares, and they do not preclude the firm from choosing the average level of amenities endogenously.

[7]Within-firm productivity is identified (up to a normalization) by comparing the relative MRPL across worker types within the same firm. The returns-to-scale parameter, which captures curvature in the production function, is identified by comparing a linear approximation to revenue calculated using labor inputs to the observed revenue in the data. Finally, TFP is identified using the equation for the production function, assuming competition in the output market and normalizing the output price to 1.

[8]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.

[9]Using the CEEDD, Dostie et al. (2023) estimate an AKM model to decompose the immigrant-native pay gap in Canada into individual and firm-level components. I follow Dostie et al. (2023) closely when cleaning the data, with one exception: I obtain the threshold used to define full-time equivalent (FTE) workers from Li et al. (2023).

range between 3 and 6 (Card, 2022; Manning, 2021). According to the model, this elasticity implies an average wage markdown of 82%, meaning that workers earn 82% of their MRPL on average. However, 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 imigrants have a labor-supply elasticity of 5.09, which is higher and statistically different from the labor-supply elasticities for family-class immigrants (3.85) and refugees (3.20). The labor-supply elasticity for economic immigrants implies a markdowns of 80%, which is higher and statistically different from the markdowns for family class immigrants (75%) and refugees (73%).

The second key finding relates to the sources of immigrants' differential exposure to labor market power: labor market concentration and job differentiation. Immigrants are exposed to more between-market labor market concentration, while natives are exposed to more within-market labor market concentration. The between-market labor market concentration tends to dominate the within-market concentration, leading to higher exposure to labor market concentration for immigrants relative to natives. In addition, jobs tend to be more differentiated for immigrants relative to natives. As a result, immigrants' labor supply is more inelastic relative to natives'.

The third key finding relates to differences in firm productivity between immigrants and natives. On average, immigrants are less productive compared to natives in the same firm, suggesting significant within-firm differences in productivity that increase the immigrant-native earnings gap. On the other hand, immigrants tend to work at firms with higher TFP and returns to scale, implying that between-firm differences productivity attenuate the gap. Interestingly, economic-class immigrants tend to work at firms with higher TFP and returns to scale compared to other immigrants and natives, suggesting that their higher earnings are in part a reflection of sorting into more productive firms.

In Section 6, I discuss the counterfactual analyses used to gauge the relative contributions of labor supply and demand factors to the immigrant-native pay gap. These counterfactual analyses proceed as follows. First, I eliminate sources of heterogeneity in model primitives (labor supply or demand factors). Then, I solve for equilibrium wages and employment and document the effects on the immigrant-native earnings gap. Importantly, the counterfactual analyses take into account general equilibrium effects.

There are three main takeaways from the counterfactual analyses. First, when we eliminate heterogeneity in between-firm productivity, the immigrant-native pay gap increases.

This result is consistent with the descriptive findings reported in Section 5, where we found that immigrants tend to work at more productive firms compared to natives. By eliminating heterogeneity in between-firm productivity *within cities*, we find that the immigrant-native pay gap decreases. This suggests that immigrants tend to sort into cities with more productive firms compared to natives, but within the same city, immigrants tend to work at less productive firms. Second, if we eliminate heterogeneity in within-firm productivity, the gap decreases. This is also consistent with the findings in Section 5, where we found that immigrants tend to be less productive than natives within the same firm.[10] Finally, if we eliminate *all* heterogeneity in firm productivity, the gap widens to 24%. After eliminating all production function heterogeneity, the remaining gap is driven by differences in labor supply curves between immigrants and natives. These differences in labor supply reflect labor market power and compensating differentials.[11]

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 (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 for understanding the immigrant-native pay gap. Second, it introduces a novel decomposition of the pay gap into labor supply and demand factors – an approach to understanding the immigrant-native pay gap that, to my knowledge, has not been explored in the existing literature.

[10] The relationship between within-firm productivity and the immigrant-native pay gap depends on interaction effects with other sources of heterogeneity in the model. Following the language in CKMM, this implies that the relationship between within-firm productivity and the immigrant-native pay gap is "not robust."

[11] In the model, virtually all firms have decreasing returns to scale, and curvature in the production function generates compensating differentials. This occurs because as firms grow larger, the MRPL falls due to decreasing returns to scale, resulting in wage penalties for working at desirable firms. Large firms also have greater market share, decreasing their markdowns and generating compensating differentials.

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.[12] 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).[13]

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 (CMA/CA) and industry (2-digit NAICS). 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.

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.,

[12] 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.

[13] 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.

$\log(u_{k0t}) = 0$. Define $v_{kjt} \equiv \log \beta_k w_{kjt} + \log u_{kjt}$.

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 $\frac{1}{\sigma_{kg}} = \sqrt{1 - \mathrm{corr}(\varepsilon_{ijt}, \varepsilon_{ij't})}$ 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.[14] Additionally, a higher degree of horizontal differentiation within a market enhances labor market power because workers have fewer desirable job alternatives.

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 $\sigma_{kg} = 1$, firms are perceived as independent by the worker, whereas if $\sigma_{kg} = \infty$, firms within the same market are viewed as perfect substitutes. Thus, as σ_{kg} increases, firms become more similar from the worker's perspective, implying that workers perceive more job alternatives when firms are substitutes within the local market. Consequently, a higher σ_{kg} lower's a firm's labor market power. 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 reduces employer differentiation, increases the availability of suitable job alternatives for the worker, and lower's the firm's 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

[14] The parameter u_{kjt} also reflects compensating differentials.

in the immigration literature that immigrants prefer to live in ethnic enclaves.[15] 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:

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

The derivative of $G_{k.}(v_{k.t})$ with respect to v_{kjt} can be calculated from equation 4 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 at time t:

$$\log\frac{s_{kjt}}{s_{k0t}} = \beta_k\log\frac{w_{kjt}}{w_{k0t}} + \tilde{\sigma}_{kg}\log s_{kjt|g} + \log u_{kjt}, \tag{5}$$

where $\frac{s_{kjt}}{s_{k0jt}}$ is the ratio of firm j's share of type-k 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 market share (often called the "inside share"), which is the firm's share of type-k employment in local labor market g at time t. The term $\tilde{\sigma}_{kg} \equiv (1 - 1/\sigma_{kg})$, and $\log u_{kjt}$ represents the deterministic preference for amenities common to all workers of type k at firm j in period t.

Note that the labor supply elasticity can be expressed as:

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

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

Equation 6 shows that the labor supply elasticity is a function of β_k, σ_{kg}, market share $s_{kjt|g}$, and the share of total workers s_{kjt}. Lower β_k and σ_{kg} imply more horizontal differentiation for workers of type k, which leads to a lower $\mathcal{E}_{kjt}$. A lower $\mathcal{E}_{kjt}$ results in a lower markdown (equation 9), indicating a higher degree of wage-setting power.[16] Equation 6 also shows that labor-supply elasticities vary at the firm level due to heterogeneity in market shares.

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 the firm. Assume that firm j at time t has the following production technology:

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

where $\tilde{\gamma}_{kjt} \equiv \theta_{jt}\gamma_{kjt}$ 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 within the same firm.[17]

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 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

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

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

function approximates the production process quite well. Furthermore, a substantial literature on the impact of immigration on native earnings finds that immigrants and natives are often perfect substitutes (e.g., Borjas et al. (2012)).

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.[18] Formally, in period t, firm j chooses the vector of wages $\vec{w}_{jt}$ to maximize

$$P_{jt}F_{jt}(l_{\cdot jt}) - \sum_{k \in \mathcal{K}} w_{kjt} l_{kjt}, \tag{8}$$

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:

$$w_{kjt} = \underbrace{P_{jt}\frac{\partial F_{jt}(l_{\cdot jt})}{\partial l_{kjt}}}_{\text{MRPL}_{kjt}} \times \underbrace{\frac{\mathcal{E}_{kjt}}{1 + \mathcal{E}_{kjt}}}_{\text{md}_{kjt}}, \tag{9}$$

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.

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

$$\overline{x}_{k \in \mathcal{S}} \equiv \sum_{j \in \mathcal{J}} \sum_{t=2002}^{2019} \sum_{k \in \mathcal{S}} \omega_{kjt} x_{kjt}, \tag{10}$$

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,

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

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 earnings gap between immigrants and native is defined as:

$$\text{Earnings Gap} \equiv \frac{\overline{w}_{k\in\text{Native}} - \overline{w}_{k\in\text{Immigrant}}}{\overline{w}_{k\in\text{Native}}}, \tag{11}$$

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

We identify the labor supply parameters by estimating the quasi-supply function (equation 5. Using equation 5, it is possible to account for oligopsony and strategic interactions in wage-setting by directly controlling for the market share.[19] The remaining identification challenge is that wages and the 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 earnings gap, as immigrants may have different location preferences compared to non-immigrants (e.g., choosing to live and work in immigrant enclaves). Thus, estimating equation (5) using Ordinary Least Squares (OLS) would result in biased estimates of β_k and σ_{kg}.

To identify β_k and σ_{kg} in equation (5), I follow CKMM and adopt an instrumental variables (IV) approach using "internal panel instruments" similar to Lamadon et al. (2022). Intuitively, the main assumptions are that innovations in productivity are persistent, while innovations in deterministic preferences for amenities are transitory. Importantly, these identification 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

[19] 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.

MA(1) process. Then, write the labor-supply equation 5 in "long changes":

$$\Delta_{long}\left[\log \frac{s_{kjgt}}{s_{k0t}}\right] = \beta_k \Delta_{long}\left[\log \frac{w_{kjt}}{w_{k0t}}\right] + \tilde{\sigma}_{kgt}\Delta_{long}\left[\log s_{kj|gt}\right] + \Delta_{long}[\log u_{kjt}], \tag{12}$$

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}. We use the following productivity-related variables to construct the internal 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 $\log\left(\sum_{\{h\in C_{jt}|h\neq k\}} s_{hjt|g}\right)$. For each of these productivity-related variables, we construct the instrument as the "short" (one-period) change:

$$\Delta_{short}z_{kjt} = z_{kjt} - z_{kjt-1}, \tag{13}$$

where the Δ_{short} operator is the change in the productivity-related variable z_{kjt} over one period. With the assumption that $\log u_{kjt}$ follows an MA(1) process and that productivity $\tilde{\gamma}_{lkjt}$ follows an AR(1) process, these short changes in productivity variables will be correlated with long changes in wages and the market share but uncorrelated with long changes in deterministic preferences for amenities. This ensures that the exclusion restriction and relevance condition hold, identifying β_k and σ_{kg}. In practice, equation 12 is estimated using Two-Stage Least Squares (2SLS).

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 other instruments used in the monopsony literature to identify firm-specific labor-supply parameters.[20]

3.2 Labor demand parameters

Given the labor supply parameters, we can calculate the labor-supply elasticity $\mathcal{E}_{kjt}$ using equation 6 and the markdown $\text{md}_{kjt} = \frac{\mathcal{E}_{kjt}}{1+\mathcal{E}_{kjt}}$. Using the first order condition of the firm (equation 9), we can identify the marginal revenue product of labor (MRPL) using:

$$\text{MRPL}_{kjt} = \frac{1+\mathcal{E}_{kjt}}{\mathcal{E}_{kjt}} w_{kjt}. \tag{14}$$

Next, we can use the first-order condition (FOC) in the firm's profit maximization prob-

[20] 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 similar results.

lem:

$$\text{MRPL}_{kjt} = P_{jt}\alpha_{jt}\tilde{\theta}_{jt}\gamma_{kjt}\left(\sum_{k\in C_{jt}}\tilde{\gamma}_{kjt}l_{kjt}\right)^{\alpha_{jt}-1}. \tag{15}$$

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

$$\frac{\text{MRPL}_{kjt}}{\text{MRPL}_{hjt}} = \frac{\gamma_{kjt}}{\gamma_{hjt}}. \tag{16}$$

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

$$1 = \sum_{k\in C_{jt}}\frac{\gamma_{hjt}\text{MRPL}_{kjt}}{\text{MRPL}_{hjt}} \tag{17}$$

which implies

$$\gamma_{hjt} = \frac{\text{MRPL}_{hjt}}{\sum_{k\in C_{jt}}\text{MRPL}_{kjt}}. \tag{18}$$

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 firm.

To identify α_{jt}, note that we can write the FOC for worker type k as:

$$\text{MRPL}_{kjt} = \alpha_{jt}\gamma_{kjt}\frac{R_{jt}}{\sum_{h\in C_{jt}}\gamma_{hjt}l_{hjt}}, \tag{19}$$

where R_{jt} is the revenue of firm j at time t. Note that R_{jt} is observed in the data, and thus everything in equation 19 is known except for α_{jt}. Plugging in the expression for γ_{kjt} into 19 and re-arranging, we get the following equation which is used to identify α_{jt}:

$$\alpha_{jt} = \frac{\sum_{h\in C_{jt}}\text{MRPL}_{hjt}l_{hjt}}{R_{jt}}. \tag{20}$$

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

Finally, to identify TFP $\tilde{\theta}_{jt}$, we must assume perfect competition in the output market (which implies constant output price) and normalize the price of output to 1. Then, we can

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

use the structural equation for revenue to identify TFP:

$$R_{jt} = \tilde{\theta}_{jt} \left(\sum_{k \in C_{jt}} \gamma_{kjt} l_{kjt} \right)^{\alpha_{jt}}, \tag{21}$$

which implies:

$$\tilde{\theta}_{jt} = \frac{R_{jt}}{\left(\sum_{h \in C_{jt}} \gamma_{hjt} l_{hjt} \right)^{\alpha_{jt}}}. \tag{22}$$

4 Data

To estimate the model, I use data from the Canadian Employer-Employee Dynamics Database (CEEDD), a comprehensive matched employer-employee dataset maintained by Statistics Canada. The CEEDD covers the near universe of individuals and firms in Canada from 2002 to 2019. This dataset integrates several sources: the T1 personal master file (T1PMF), which provides demographic information such as age, location, marital status, and gender; the T4 database linked to the record of employment (T4ROE), which includes job-level data on earnings and industry; the National Accounts Longitudinal Microdata File (NALMF), which contains details on firms' financial positions; and the Immigrant Longitudinal Database (IMDB), which offers rich demographic information on immigrants, including country of origin and 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.[22]

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

[22] 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).

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.[23] 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 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

[23]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).

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 model primitives, I begin with discussing the relevance condition associated with the IV approach. As mentioned in section 3, one of the main identification assumption relates to the persistence of productivity shocks, which relates to the relevant condition of the IV. The short changes in productivity-related variables are indeed correlated with long changes in wages and market shares, as indicated by the first stage results presented in table A1. Most F-statistics exceed 10, with the majority surpassing 100. 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 immigrants indeed have different distributions of stochastic preferences for amenities compared to native-born workers. Table 2 presents employment-weighted averages of the estimated the 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 6). We find that immigrants have a higher average β_k (0.70) compared to natives (0.56), and this difference is statistically significant.[26] Conversely, immigrants have a lower average σ_{kg} (6.81), compared to natives (11.73), a statistically significant difference.[27] Figure A8 displays the

[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 10.

[26]The higher β_k among immigrants suggests that match-specific amenities are less significant for immigrants compared to natives, indicating that immigrants prioritize wages over amenities more than natives do.

[27]The lower σ_{kg} for immigrants suggests that they have fewer job alternatives within the same labor market compared to natives, implying that natives are more likely to find an alternative job within the same market that is a close substitute to their current employment.

values of β_k and figure A9 displays the average σ_{kg} for each k-group.

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 0.13, indicating generally decreasing returns to scale for firms.[28] Comparing immigrants and natives, we find that both of the firm-level productivity parameters tend to be higher for immigrants compared to natives, a result that is entirely due to sorting across firms. Immigrants have an average α_{jt} of 0.16, compared to 0.12 for natives, and this difference is statistically significant. The average $\log \tilde{\theta}_{jt}$ is also higher for immigrants on average (17.68) compared to natives (17.67), a 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 famly-class immigrants. Figure A10 displays the average α_{jt} and Figure A11 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:

$$\log(\hat{\gamma}_{kjt}) = \Gamma_k + \psi_{jt} + e^{\gamma}_{kjt}, \tag{23}$$

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 6. The results suggest a considerable amount of wage-setting

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

power in Canada, with the average firm-specific labor-supply elasticity equal to 5.25.[29] The results also suggest that immigrants have more inelastic firm-specific labor supply compared to natives, with average firm-specific labor supply elasticity for immigrants (4.4) statistically different from the average for natives (5.45).[30]

Figure A19 shows heterogeneity in firm-specific labor-supply elasticities across immigration categories, with those in the economic-class having the highest firm-specific labor supply 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 firm-specific labor supply elasticity for economic class immigrants is not statistically different from the average firm-specific labor supply elasticities for natives. The ordering of firm-specific 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 A4 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 the average labor supply elasticity of 5.09 for native-born women, a statistically significant difference. 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 A8 and A9. 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 9. 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 signficant markdown gap of approximately 7 percentage points.

Looking at the heterogeneity by immigration category in Figure A19, we find that eco-

[29]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).

[30]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 10. 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.

nomic class immigrants have an average markdown of 0.80, family class immigrants have a markdown of 0.75, and refugees a markdown of 0.73, all statistically significantly different from one another. These differences in markdowns mirror the variations in elasticities across the different immigration categories, as discussed above. Figure A5 displays the markdowns for each k-group.

There is some heterogeneity in labor supply elasticities and markdowns exists across provinces, with lower values observed in Quebec, the Prairies, and Atlantic Canada (see Figure A1). These results are intuitive, suggesting that workers in Ontario and British Columbia have more suitable job alternatives compared to workers in other provinces.[31] In the Prairies and Atlantic provinces, immigrants face markdowns that are 15 percentage points lower on average than those of native-born workers, suggesting that firms exert substantially more monopsony power over immigrants in these areas. In Quebec, the markdown gap is 10 percentage points, indicating that firms also hold considerably more monopsony power over immigrant workers compared to native-born workers in Québecois labor markets. In Ontario and British Columbia, the average difference in markdwowns 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.[32] The GCI has the form:

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

[32] 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.

$$GCI_{kt} \equiv \left[\prod_{g \in \mathcal{G}} \left(\underbrace{\exp \left\{ \sum_{j \in \mathcal{J}_g} s_{kjt|g} \log s_{kjt|g} \right\}}_{\text{Within-group concentration index (WGCI)}} \right)^{\frac{s_{kgt}}{\sigma_{kg}}} \right] \times \underbrace{\left[\exp \left\{ \sum_{g \in \mathcal{G}} s_{kgt} \log s_{kgt} \right\} \right]}_{\text{Between-group concentration index (BGCI)}}, \tag{24}$$

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 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 market share, immigrants supply labor more inelastically compared to natives.[33] 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. Armed with the estimates of β_k and σ_{kg}, I use equation 5 to recover the deterministic preferences for amenities:

$$\widehat{\log u_{kjt}} = \log \frac{s_{kjt}}{s_{k0t}} - \hat{\beta}_k \log \frac{w_{kjt}}{w_{k0t}} - \widehat{\widetilde{\sigma_{kg}}} \log s_{kjt|g}. \tag{25}$$

Then, to investigate which factors are correlated with the deterministic preferences, I esti-

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

mate the following regression:

$$\widehat{\log u_{kjt}} = X_{jt}'\beta^u + \psi_n^u + \psi_p^u + e_{kjt}^u, \quad (26)$$

where $\widehat{\log u_{kjt}}$ are the estimated values of the vertical amenity term obtained from equation (25), 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 26 separately for immigrants and natives to investigate how immigrants' deterministic preferences for amenities differ systematically from natives' deterministic preferences. The results, presented in Figure A16, 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 A16, 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 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 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 26 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:

$$\hat{\psi}_{kn}^u = \eta_0 + \eta_1 x_n + \nu_{kn}^u, \quad (27)$$

where x_n is the rate of illnesses or injuries in industry n and ν_{kn}^u is the error term.[34] The results are reported in Table A2 (Column 1). 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 at firms that work in industries with safer environments. Immigrants tend to work in work environments that are less safe than natives (e.g. 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

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

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 26 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 26 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 in accounting for the variation in $\log(u_{kjt})$.

Figure 7 shows that province fixed effects explain a larger share of the variance in preferences for amenities for immigrants compared to natives. This finding is consistent with immigrants 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 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 examine the relative contributions of labor supply and demand factors to the immigrant-native earnings gap. The objective is to use a general equilibrium framework to understand how heterogeneity in model primitives affects earnings inequality between immigrants and natives.[35] To conduct these counterfactual analyses, I follow the decomposition approach in CKMM and Taber and Vejlin (2020). Specifically, I eliminate heterogeneity in model primitives and examine the impact on earnings inequality and other equilibrium

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

outcomes, including wage markdowns.

I conduct counterfactuals where I only eliminate heterogeneity in between-firm productivity (α_{jt}, $\tilde{\theta}_{jt}$) or only eliminate heterogeneity in within-firm productivity (γ_{kjt}) to decompose differences in MRPL between immigrants and natives into between- and within-firm components. To investigate the sources of immigrants' higher between-firm productivity, I conduct a counterfactual analysis where I eliminate heterogeneity in between-firm productivity within cities (but not between them). Next, I conduct a counterfactual where heterogeneity in *all* productivity parameters (α_{jt}, $\tilde{\theta}_{jt}$, and γ_{kjt}) is eliminated. In this counterfactual scenario, the remaining immigrant-native earning gap arises due to heterogeneity in labor-supply parameters. Moreover, since all production function parameters are equal in this scenario, any variation in MRPL across worker types and firms is due to decreasing returns in the production function and worker sorting. Firms will have high levels of employment due to high deterministic preferences for amenities (u_{kjt}), lower MRPL due to decreasing returns to scale, and therefore lower wages. To investigate the role of curvature in the production function in generating compensating differentials, in the final counterfactual scenario I set $\alpha_{jt} = 1$ (while simultaneously eliminating heterogeneity in γ_{kjt} and $\tilde{\theta}_{jt}$).

In summary, I investigate the following counterfactual scenarios:

A. No heterogeneity in between-firm productivity, i.e., $\alpha_{jt} = \bar{\alpha}$ and $\theta_{jt} = \bar{\theta}$ for all j, t.[36]

B. No heterogeneity in between-firm productivity *within cities*, i.e., $\alpha_{jt} = \bar{\alpha}_c$ and $\theta_{jt} = \bar{\theta}_c$ j, t, c.

C. No heterogeneity in within-firm productivity, i.e., $\gamma_{kjt} = \bar{\gamma}$ for all k, j, t.

D. No heterogeneity in all productivity parameters (combination of scenario 1 and 2).

E. No heterogeneity in $\tilde{\theta}_{jt}$ and γ_{kjt}, and $\alpha_{jt} = 1$ for all j, t.

To solve for equilibrium wages and shares under each of the various counterfactual scenarios, I use the under-relaxed Jacobi iteration described in CKMM. The procedure 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:

$$\delta_{kjt}(w_t) \equiv w_{kjt} - \tilde{\theta}_{jt}\alpha_{jt}\gamma_{jt}\left(\sum_{k \in C_{jt}} \gamma_{kjt} l_{kjt}(w_t)\right)^{\alpha_{jt}-1} \frac{\mathcal{E}_{kjt}(w_t)}{\mathcal{E}_{kjt}(w_t)+1}, \tag{28}$$

[36]Here, $\bar{\alpha}$ and $\bar{\theta}$ refer to the medians of the distributions of those parameters. I choose the medians here because the distributions are highly skewed. Note that $\overline{\alpha} < 1$, so that all firms have decreasing returns to scale in this counterfactual scenario.

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

This algorithm converges to the unique equilibrium vector of wages (Chan et al., 2024).

6.2 Counterfactual Results

We begin by eliminating heterogeneity in between-firm productivity parameters α_{jt} and $\tilde{\theta}_{jt}$ (scenario A). In Table 5, we see that this increases the immigrant-native earnings gap by 9 pp to 25%. This is consistent with the findings in section 5.1, where immigrants were found to have higher α_{jt} and higher $\tilde{\theta}_{jt}$ compared to natives. To investigate the sources of these between-firm productivity differences, we next turn to a counterfactual scenario where all heterogeneity in the between-firm productivity parameters α_{jt} and $\tilde{\theta}_{jt}$ are eliminated *within cities*, but not between them (scenario B). We see that, relative to the true equilibrium pay gap of 16%, eliminating heterogeneity in between-firm productivity within city decreases the gap by 13 pp to 3%. The results from scenarios A and B suggest that, while immigrants tend to work at more productive firms in general, this is largely driven by immigrants living in cities where firms are more productive on average. When we look within cities, we see that immigrants tend to work at firms that have lower productivity compared to natives, which is why eliminating within-city heterogeneity in between-firm productivity decreases the pay gap, while eliminating all heterogeneity in between-firm productivity increases it.

Next, we turn to within-firm productivity and eliminate all heterogeneity in γ_{kjt} (scenario C). This significantly decreases the immigrant-native earnings gap by 26 pp to -10%. This is consistent with the findings in section 5.1, where immigrants were found to have lower within-firm productivity compared to natives. Turning to counterfactual scenario D, we eliminate heterogeneity in *all* production function parameters γ_{kjt}, $\tilde{\theta}_{jt}$, and α_{jt}, which increases the immigrant-native pay gap by 8 pp (relative to the true equilibrium) to 24%. This is only 1 pp lower than the gap in the scenario when only heterogeneity in between-firm productivity is eliminated, but 34 pp higher than the gap in the scenario when only heterogeneity in within-firm productivity is eliminated. Moreover, the immigrant-native pay gap in scenario D is entirely driven by heterogeneity in worker preferences, suggesting that labor-supply heterogeneity contributes significantly to earnings inequality between immigrants and natives.

Finally, we turn to a counterfactual scenario where there is no heterogeneity in the production function parameters $\tilde{\theta}_{jt}$, γ_{kjt}, and we also eliminate curvature in the production function by setting $\alpha_{jt} = 1$ for all j, t (scenario E). We see that the immigrant native pay gap falls to 6%. Compared to scenario D, in which we eliminate all heterogeneity in productivity (but maintain curvature in the production function), we see that the gap has fallen by 18 pp. This reduction is entirely due to a reduction in compensating differentials. To see why this is the case, note that when α_{jt} is equalized across firms (but curvature is maintained), variation in MRPL across worker types and firms is entirely due to worker sorting. Firms that are desirable (high deterministic preference u_{kjt}) will have high levels of employment, lower MRPL (due to decreasing returns to scale) and thus lower wages. Note that the equilibrium wages still reflect compensating differentials through the wage markdowns, as firms with higher market shares have lower markdowns and therefore there are wage penalties for working at desirable firms, even without curvature in the production function. Eliminating curvature in the production function therefore does not isolate for the importance of compensating differentials entirely.

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, immigrants tend to work at more productive firms relative to natives, although they are less productive on average relative to natives within the same firm. To decompose the immigrant-native pay gap into labor supply and demand factors, I conduct counterfactual analyses that account for general equilibrium effects. When all firm productivity heterogeneity is eliminated, the gap widens to 24%, highlighting the significant contribution of differences in labor supply to the immigrant-native pay gap.

References

Abowd, J., Kramarz, F., & Margolis, D. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333.

Altonji, J. G., & Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In *Immigration, trade, and the labor market*. University of Chicago Press.

Amior, M., & Manning, A. (2020). Monopsony and the wage effects of migration. *CEP Discussion Papers*.

Amior, M., & Stuhler, J. (2024). Immigration, monopsony and the distribution of firm pay.

Amo-Agyei, S. (2020). The migrant pay gap: Understanding wage differences between migrants and nationals. https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@ed_protect/@protrav/@migrant/documents/publication/wcms_763803.pdf

Arellano-Bover, J., & San, S. (2024). The role of firms and job mobility in the assimilation of immigrants: Former soviet union jews in israel.

Aydede, Y., & Dar, A. (2016). The cost of immigrants occupational mismatch and the effectiveness of postarrival policies in canada. *IZA Journal of Migration*, *5*(1), 9.

Bartolucci, C. (2014). Understanding the native-immigrant wage gap using matched employer-employee data: Evidence from germany. *ILR Review*, *67*(4), 1166–1202.

Beach, C. M., Worswick, C., & Green, A. G. (2011). Toward improving canada's skilled immigration policy: An evaluation approach. *SSRN Electronic Journal*.

Berger, D., Herkenhoff, K., & Mongey, S. (2022). Labor market power. *American Economic Review*, *112*(4), 1147–1193.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, *25*(2), 242–262.

Borjas, G. J., Grogger, J., & Hanson, G. H. (2012). Comment: On estimating elasticities of substitution. *Journal of the European Economic Association*, *10*(1), 198–210.

Bratsberg, B., Barth, E., & Raaum, O. (2006). Local unemployment and the relative wages of immigrants: Evidence from the current population surveys. *Review of Economics and Statistics*, *88*(2), 243–263.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, *19*(1), 22–64.

Card, D. (2022). Who set your wage? *American Economic Review*, *112*(4), 1075–1090.

Card, D., Cardoso, A. R., Heining, J., & Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, *36*(1), S13–S70.

Chan, M., Kroft, K., Mattana, E., & Mourifie, I. (2024). An empirical framework for maching with imperfect competition.

Chiswick, B. R., & Miller, P. W. (1995). The endogeneity between language and earnings - international analyses. *Journal of Labor Economics*, *13*(2), 246–288.

Damas de Matos, A. (2017). Firm heterogeneity and immigrant wage assimilation. *Applied Economics Letters*, *24*(9), 653–657.

Depew, B., Norlander, P., & Sorensen, T. (2017). Inter-firm mobility and return migration patterns of skilled guest workers. *Journal of Population Economics*, *30*(2), 681–721.

Dostie, B., Li, J., Card, D., & Parent, D. (2023). Employer policies and the immigrantânative earnings gap. *Journal of Econometrics*, *233*(2), 544–567.

Ferrer, A., Green, D., & Riddell, W. (2006). The effect of literacy on immigrant earnings. *Journal of human resources*, *41*(2), 380–410.

Fortin, N., Lemieux, T., & Torres, J. (2016). Foreign human capital and the earnings gap between immigrants and canadian-born workers. *Labour Economics*, *41*, 104–119.

Garin, A., & Silverio, F. (2023). How responsive are wages to firm-specific changes in labor dmeand? evidence from idiosyncratic export demand shocks. *Review of Economic Studies*.

Gyetvay, S., & Keita, S. (2024). Competition, mobility and immigration.

Hall, P. (1992). *The bootstrap and edgeworth expansion*. Springer.

Hirsch, B., & Jahn, E. (2015). Is there monopsonistic discrimination against immigrants? *ILR Review*, *68*(3), 501–528.

Hummels, D., Jorgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review*, *104*(6), 1597–1629.

Hunt, J., & Xie, B. (2019). How restricted is the job mobility of skilled temporary work visa holders? *Journal of Policy Analysis and Management*, *38*(1), 41–64.

Javdani, M., & McGee, A. (2018). Labor market mobility and the early-career outcomes of immigrant men. *IZA Journal of Migration and Development*, *8*(1), 1–28.

Kroft, K., Luo, Y., Mogstad, M., & Setzler, B. (2024). Imperfect competition and rents in labor and product markets: The case of the construction industry.

Lamadon, T., Mogstad, M., & Setzler, B. (2022). Imperfect competition, compensating differentials, and rent sharing in the US labor market. *American Economic Review*, *112*(1), 169–212.

Lay, A. M., Kosny, A., Aery, A., Flecker, K., & Smith, P. M. (2018). The occupational health and safety vulnerability of recent immigrants accessing settlement services. *Canadian Journal of Public Health*, *109*(3), 303–311.

Li, J., Dostie, B., & Simard-Duplain, G. (2023). Firm pay policies and the gender earnings gap: The mediating role of marital and family status. *ILR Review*, *76*(1), 160–188.

Manning, A. (2003). *Monopsony in motion: Imperfect competition in labor markets*. Princeton University Press.

Manning, A. (2021). Monopsony in labor markets: A review. *ILR Review*, *74*(1), 3–26.

McFadden, D. (1978). Modeling the choice of residential location. In A. Karlqvist, L. Lundqvist, J. Weibull, & F. Snickars (Eds.), *Spatial interaction theory and residential location* (pp. 75–96). North Holland.

Naidu, S., Nyarko, Y., & Wang, S.-Y. (2016). Monopsony power in migrant labor markets: Evidence from the united arab emirates. *Journal of Political Economy*, *124*(6), 1735–1792.

Oreopoulos, P. (2011). Why do skilled immigrants struggle in the labor market? a field experiment with thirteen thousand resumes. *American Economic Journal: Economic Policy*, *3*(4), 148–171.

Pendakur, K., & Woodcock, S. (2010). Glass ceilings or glass doors? wage disparity within and between firms. *Journal of Business and Economic Statistics*, *28*(1), 181–189.

Robinson, J. (1933). *The economics of imperfect competition*. Macmillan; Co.

Sharma, G. (2024). Monopsony and gender.

Skuterud, M., & Su, M. (2012). Immigrants and the dynamics of high-wage jobs. *ILR Review*, *65*(2), 377–397.

Sokolova, A., & Sorensen, T. (2021). Monopsony in labor markets: A meta-analysis. *ILR Review*, *74*(1), 27–55.

StatsCan. (2022). The daily: Immigrants make up the largest share of the population in over 150 years and continue to shape who we are as canadians. https://www150.statcan.gc.ca/n1/daily-quotidien/221026/dq221026a-eng.htm

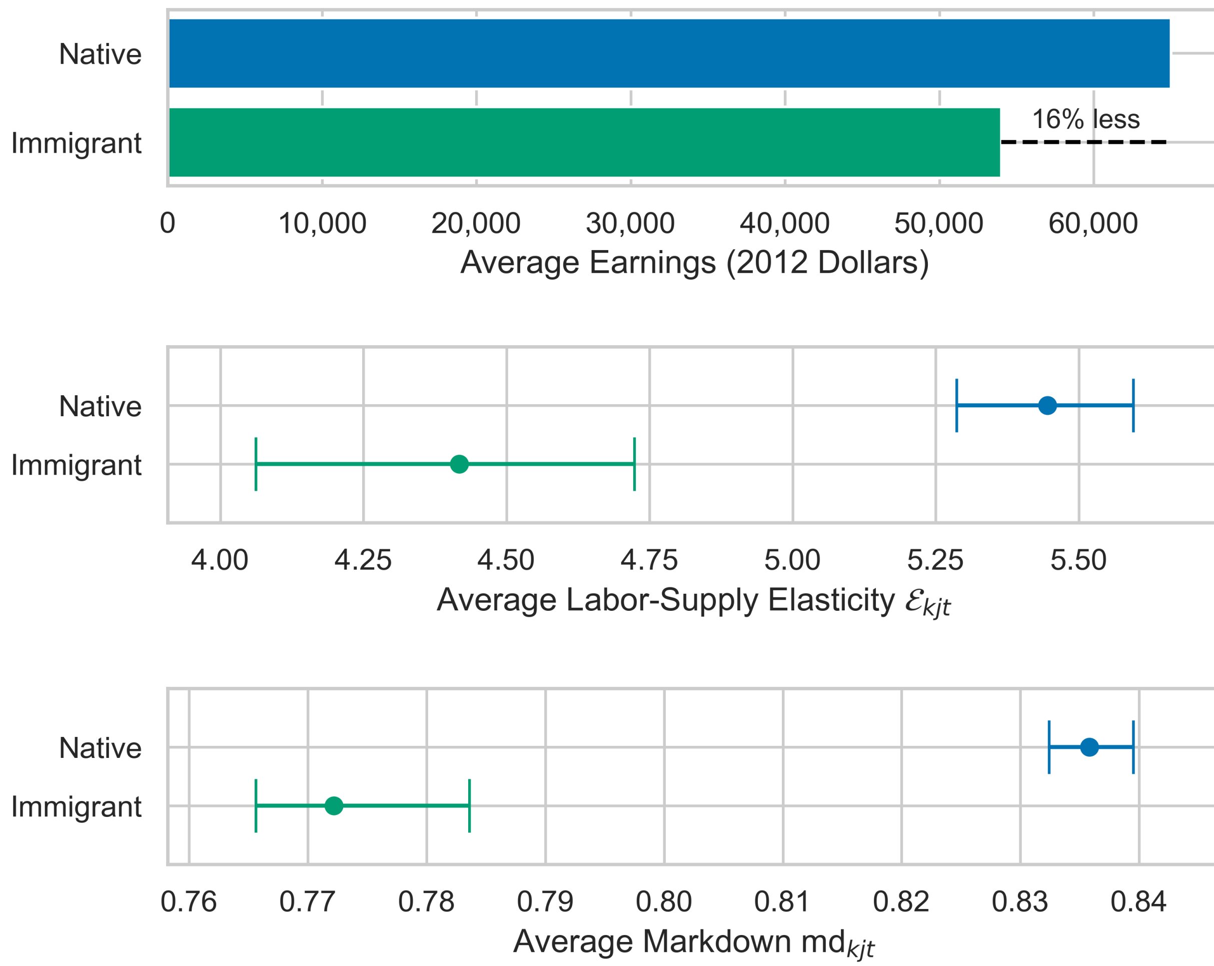
Taber, C., & Vejlin, R. (2020). Estimation of a roy/search/compensating differential model of the labor market. *Econometrica*, *88*(3), 1031–1069.

Wang, X. (2021). US permanent residency, job mobility, and earnings. *Journal of Labor Economics*, *39*(3), 639–671.

Webber, D. (2016). Firm-level monopsony and the gender pay gap. *Industrial Relations*, *55*(2), 323–345.

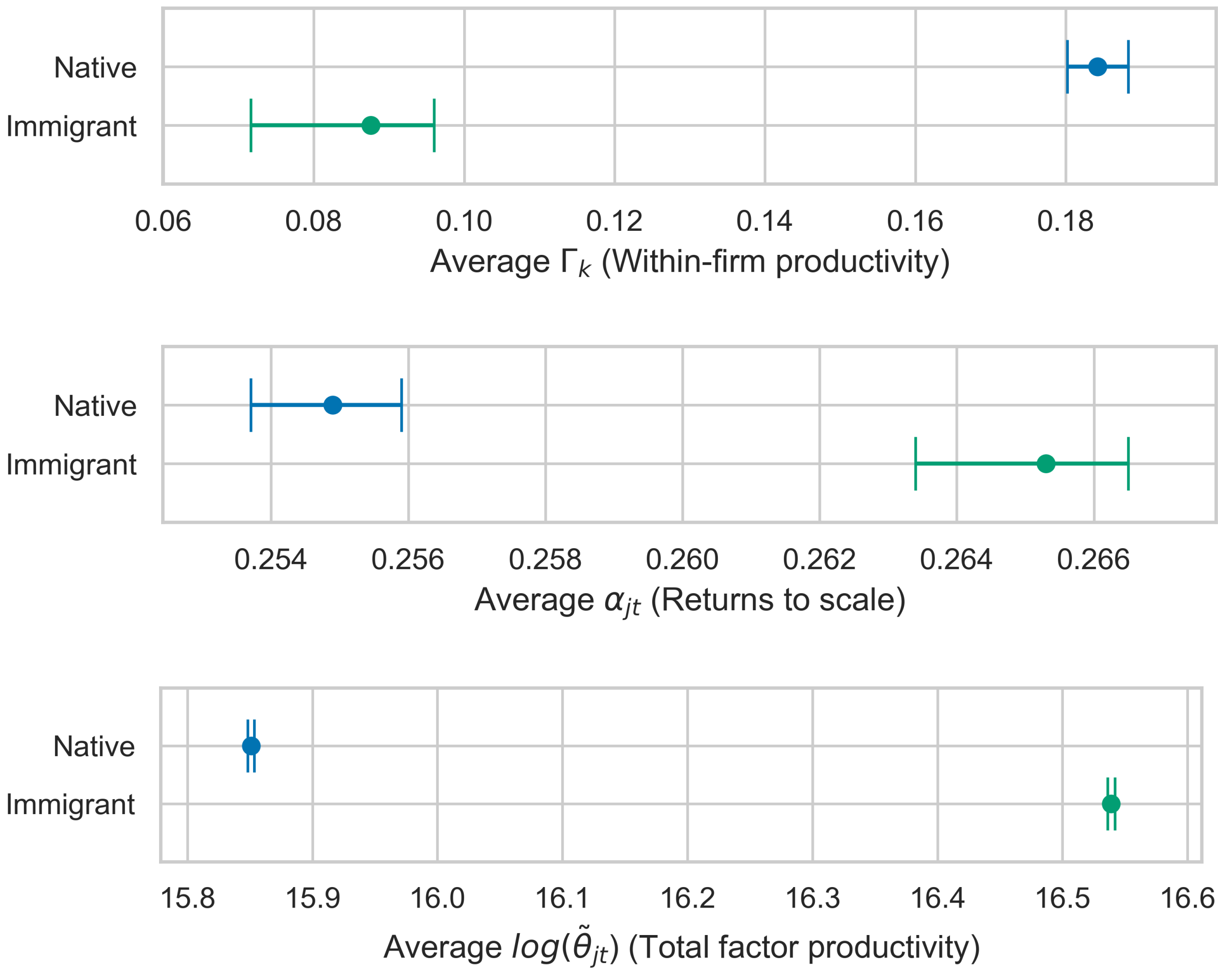
8 Figures

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



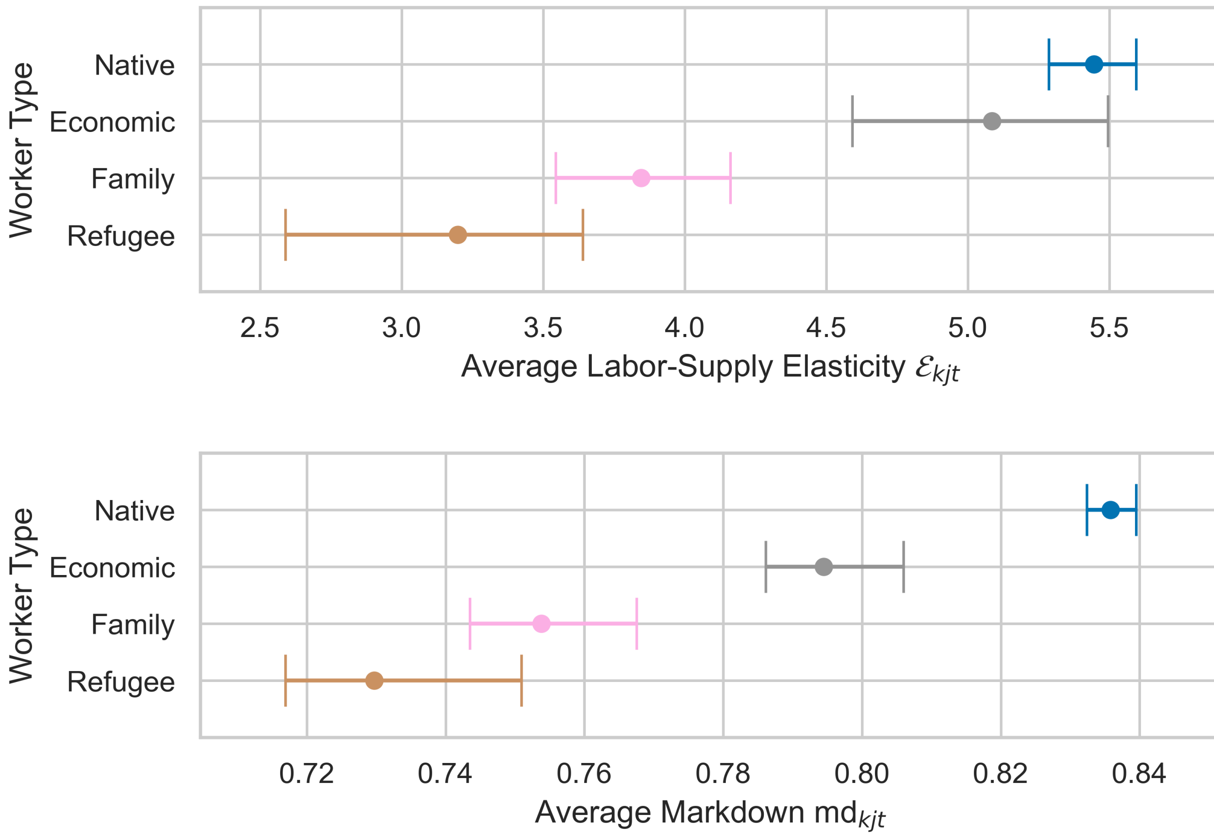
Notes: This figure presents the main estimates of labor supply elasticities and markdowns for native-born workers and immigrants. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (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 9). 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



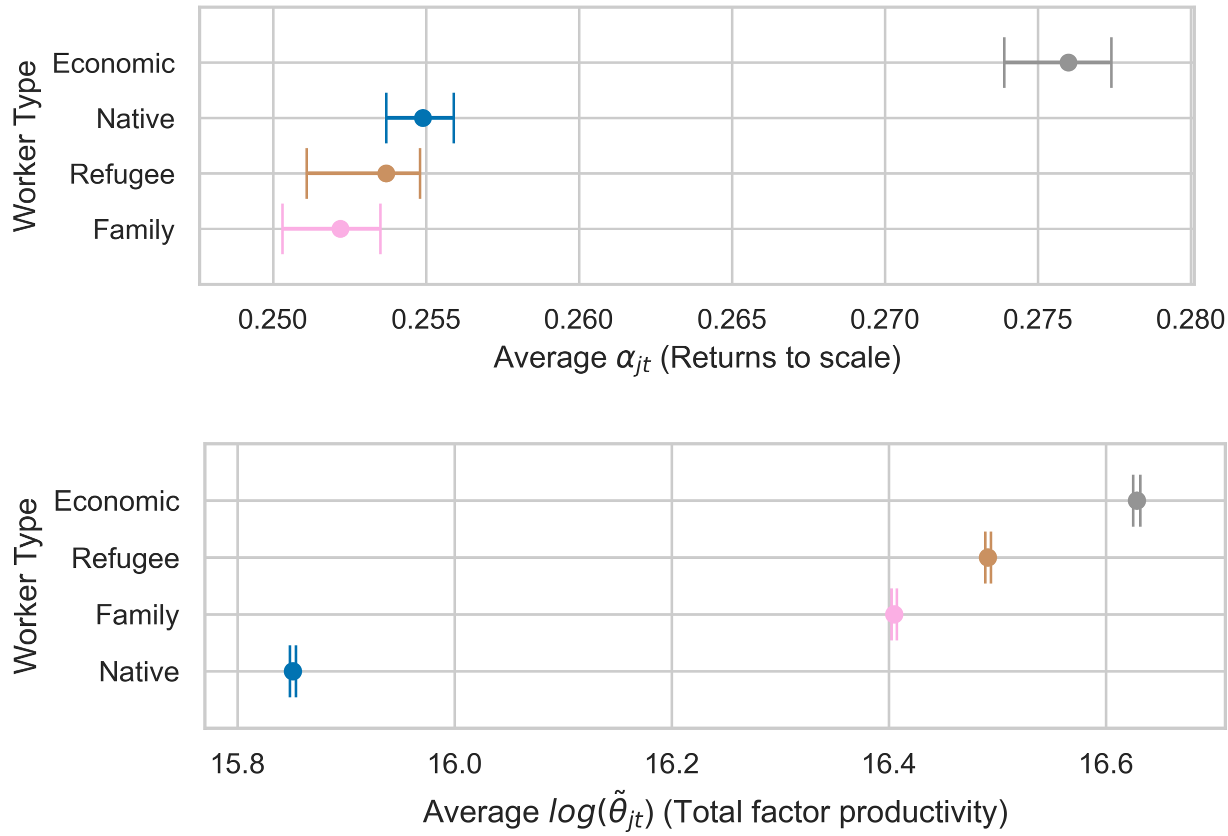
Notes: This figure presents the main estimates of the labor demand parameters. The within-firm productivity parameters γ_{kjt} are normalized within each firm so that $\sum_{k\in C_{jt}} \gamma_{kjt} = 1$, and thus, to compare the within-firm productivity parameters across firms (and construct the figure in the top panel), I first estimate equation 30 (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



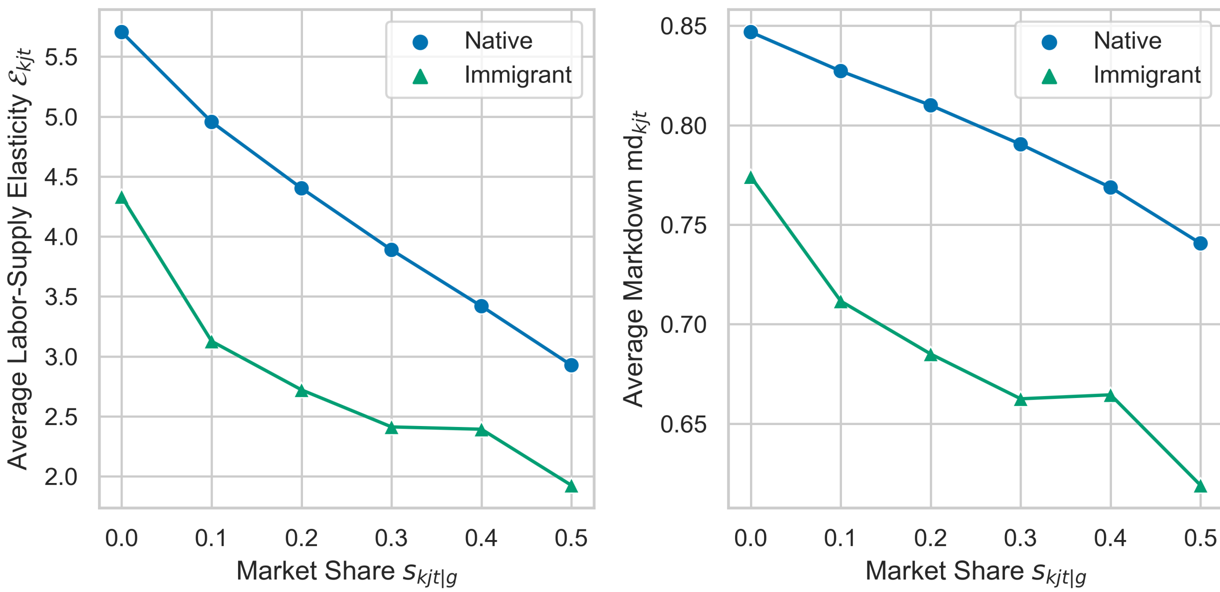
Notes: This figure presents the main estimates of labor supply elasticities and markdowns for native-born workers and three categories of immigrant workers: economic class, family class, and refugees. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined 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 9). 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



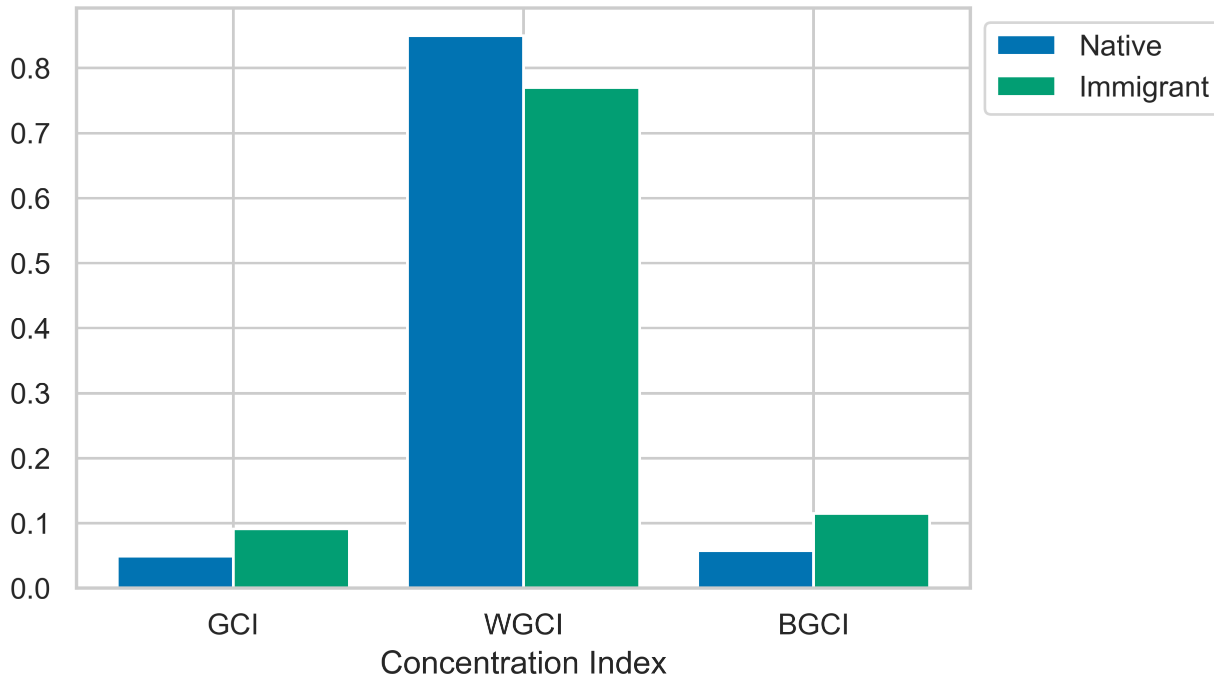
Notes: This figure presents the main estimates of the between-firm labor demand parameters for native-born workers and three categories of immigrant workers: economic class, family class, and refugees. The parameter α_{jt} captures returns to scale, and the parameter $\tilde{\theta}_{jt}$ captures total 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 $\mathrm{md}_{kjt} = \mathcal{E}_{kjt} / (1 + \mathcal{E}_{kjt})$, where $\mathcal{E}_{kjt}$ represents the labor supply elasticity (see equation 9). *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). The top panel shows these average values for immigrants and natives. The bottom panel shows average values for natives and three immigrant sub-groups: economic class, family class, and refugees. "Average" refers to the employment-weighted average in the data (see Section 2.4). *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 26 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 covarites (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. "Average" refers to 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 9). 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 7). 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 Results

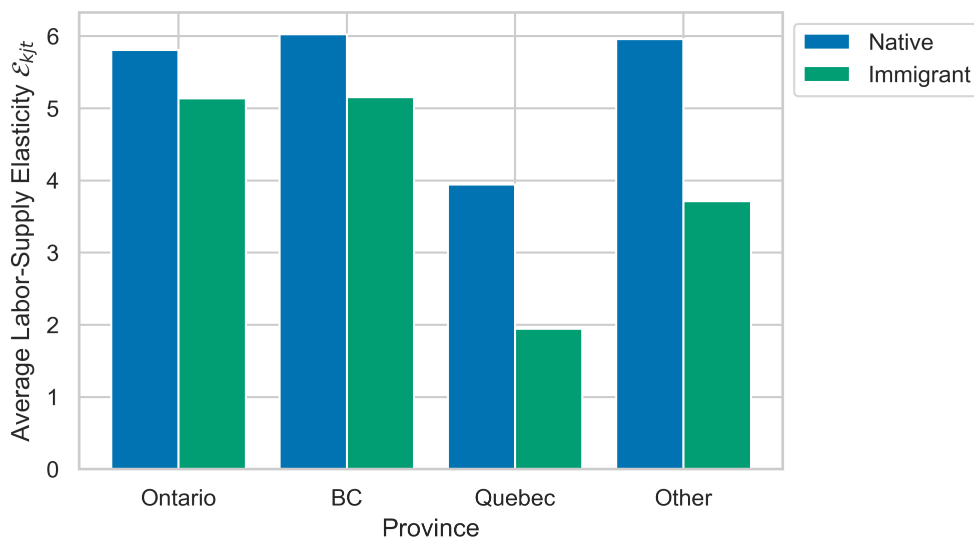
	(1)	(2)	(3)
	Imm.-Nat. Pay Gap	Markdown (Nat.)	Markdown (Imm.)
True equilibrium	16%	84%	77%
Scenario A ($\bar{\alpha}, \bar{\theta}$)	25%	85%	77%
Scenario B ($\bar{\alpha}_c, \bar{\theta}_c$)	3%	85%	79%
Scenario C ($\bar{\gamma}$)	-10%	83%	77%
Scenario D ($\bar{\alpha}, \bar{\theta}, \bar{\gamma}$)	24%	85%	78%
Scenario E ($\alpha_{jt} = 1, \bar{\theta}, \bar{\gamma}$)	6%	84%	79%

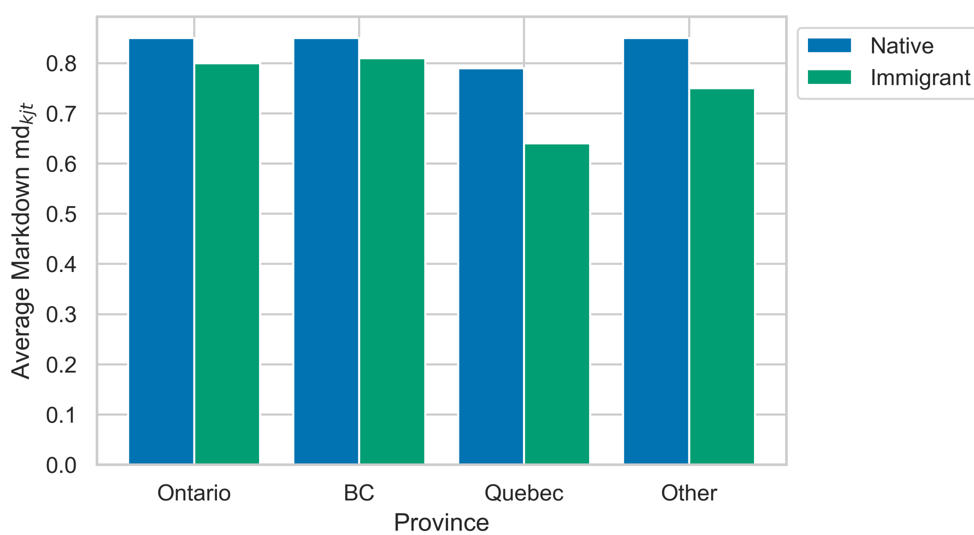
This table shows the results from the counterfactual analyses (Section 6). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL) and are equal to $\text{md}_{kjt} = \mathcal{E}_{kjt}/(1 + \mathcal{E}_{kjt})$. "Average" in this context is the employment-weighted average of markdowns in the data for natives or immigrants (see Section 2.4). For the counterfactual analyses, I eliminate heterogeneity in model primitives and document the effect on the immigrant-native pay gap $(\overline{w}_{k\in\text{nat}} - \overline{w}_{k\in\text{imm}})/\overline{w}_{k\in\text{nat}}$ (Column 1) and the average markdowns for natives (Column 2) and immigrants (Column 3). In counterfactual scenario A, I begin by eliminating heterogeneity in between-firm productivity parameters: total factor productivity (TFP) $\tilde{\theta}_{jt}$ and returns to scale α_{jt}. In counterfactual scenario B, I eliminate heterogeneity in between-firm productivity parameters within cities (but not between cities). In counterfactual scenario C, I eliminate heterogeneity in worker skill by setting $\gamma_{kjt} = \overline{\gamma}$. In counterfactual scenario D, I eliminate heterogeneity in all production function parameters. In counterfactual scenario E, I eliminate curvature in the production function $\alpha_{jt} = 1$. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Appendices

A Appendix Figures and Tables

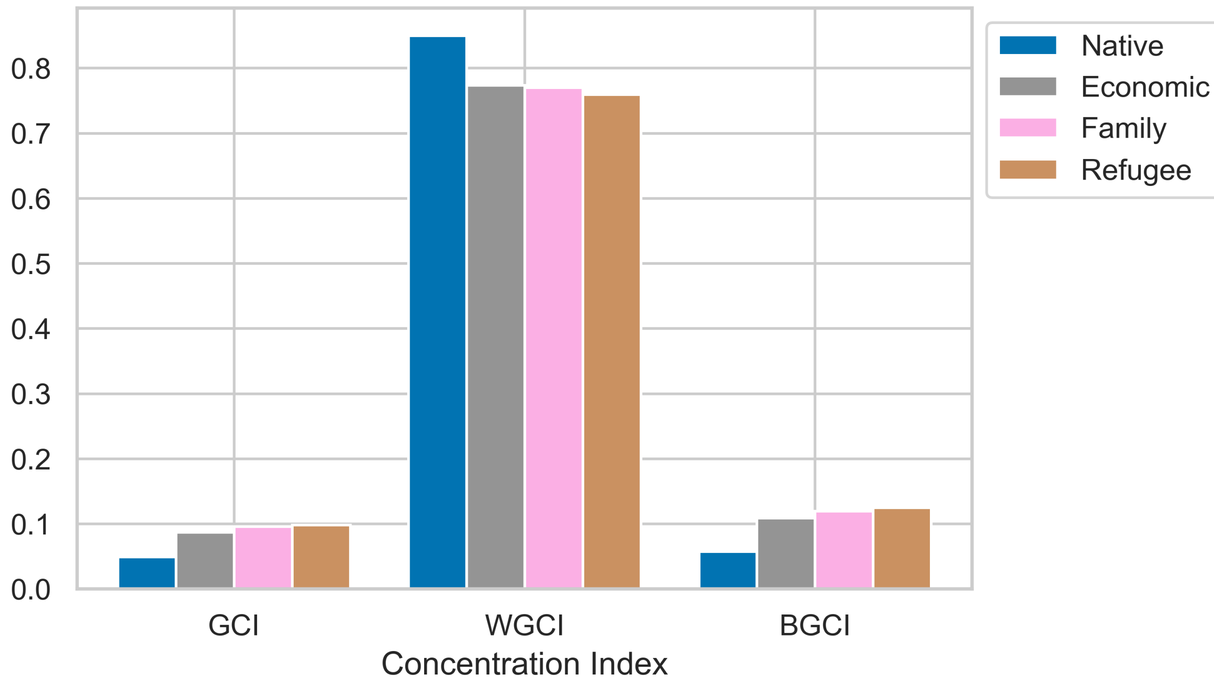
Figure A1: Heterogeneity in Labor-Supply Elasticities and Wage Markdowns by Province





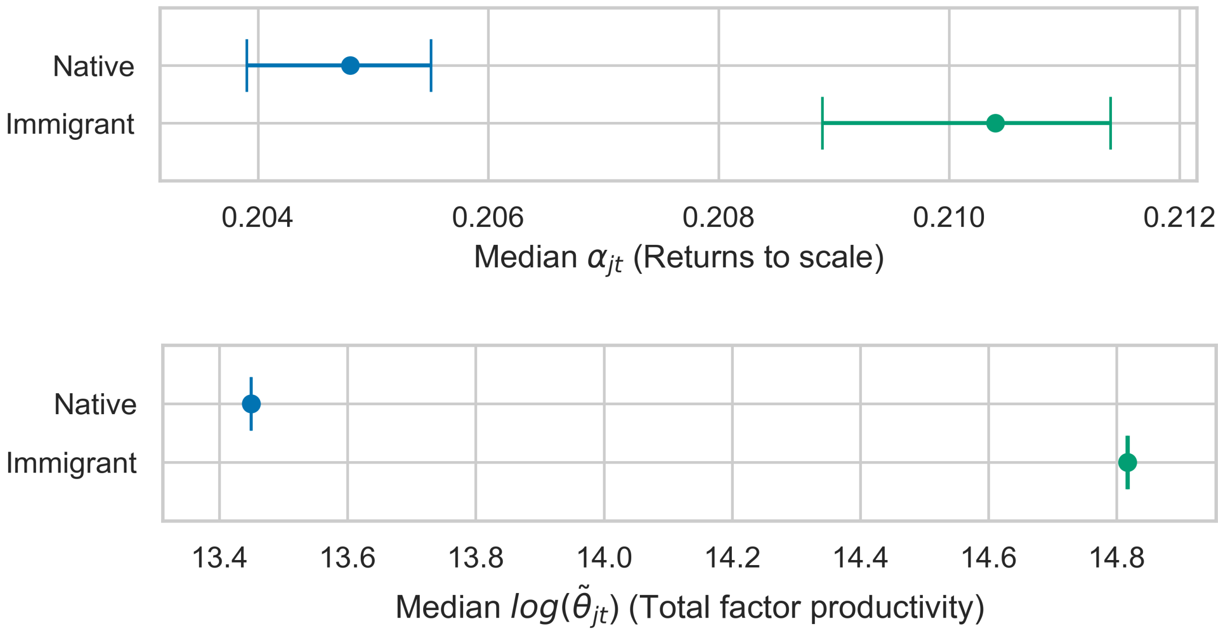
Notes: This figure presents the main estimates of labor supply elasticities and markdowns across provinces. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the 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 9). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A2: Concentration Indices



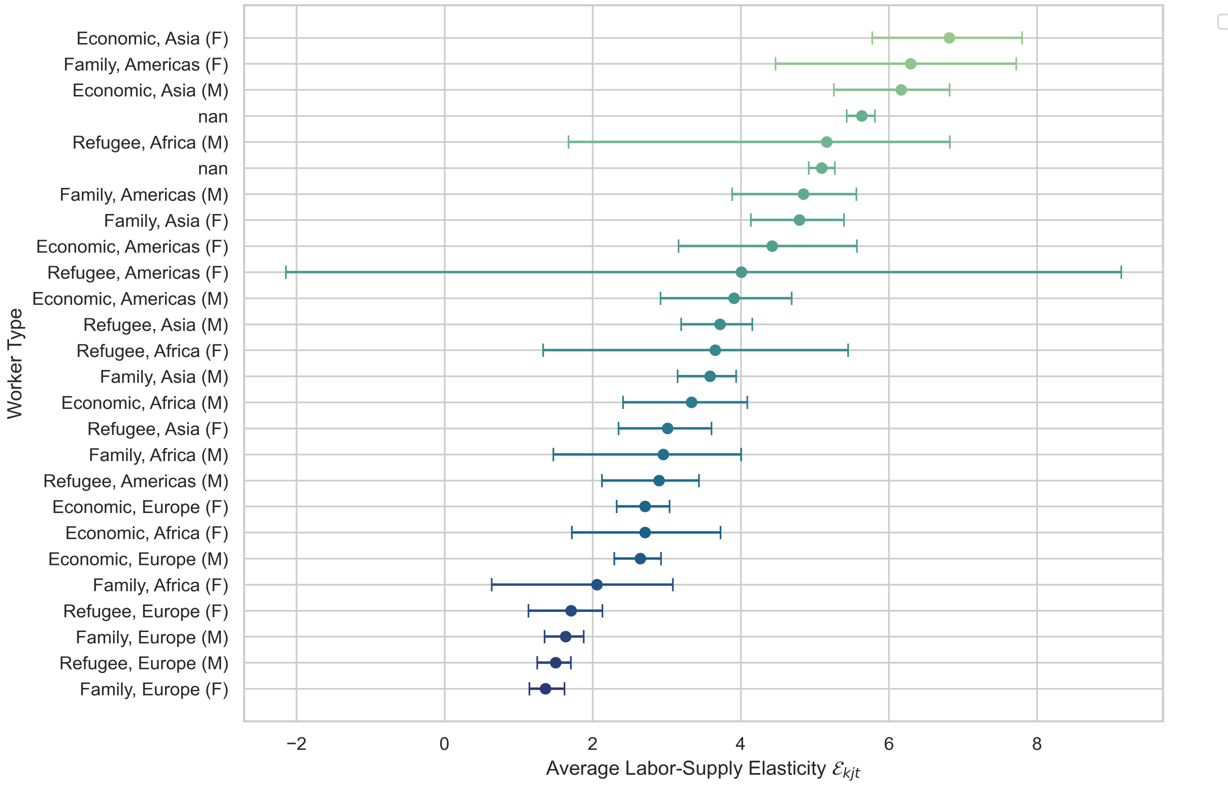
Notes: This figure presents the main estimates of the Generalized Concentration Index (GCI), Within-group Generalized Concentration Index (WGCI), and Between-group Generalized Concentration Index (BGCI) (see Section 5.3.1). The top panel shows these average values for immigrants and non-immigrants. The bottom panel shows average values for non-immigrants and three immigrant sub-groups: economic class, family class, and refugees. "Average" refers to the employment-weighted average in the data (see Section 2.4). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A3: Medians of Between-firm Productivity Parameters by Immigrant Status



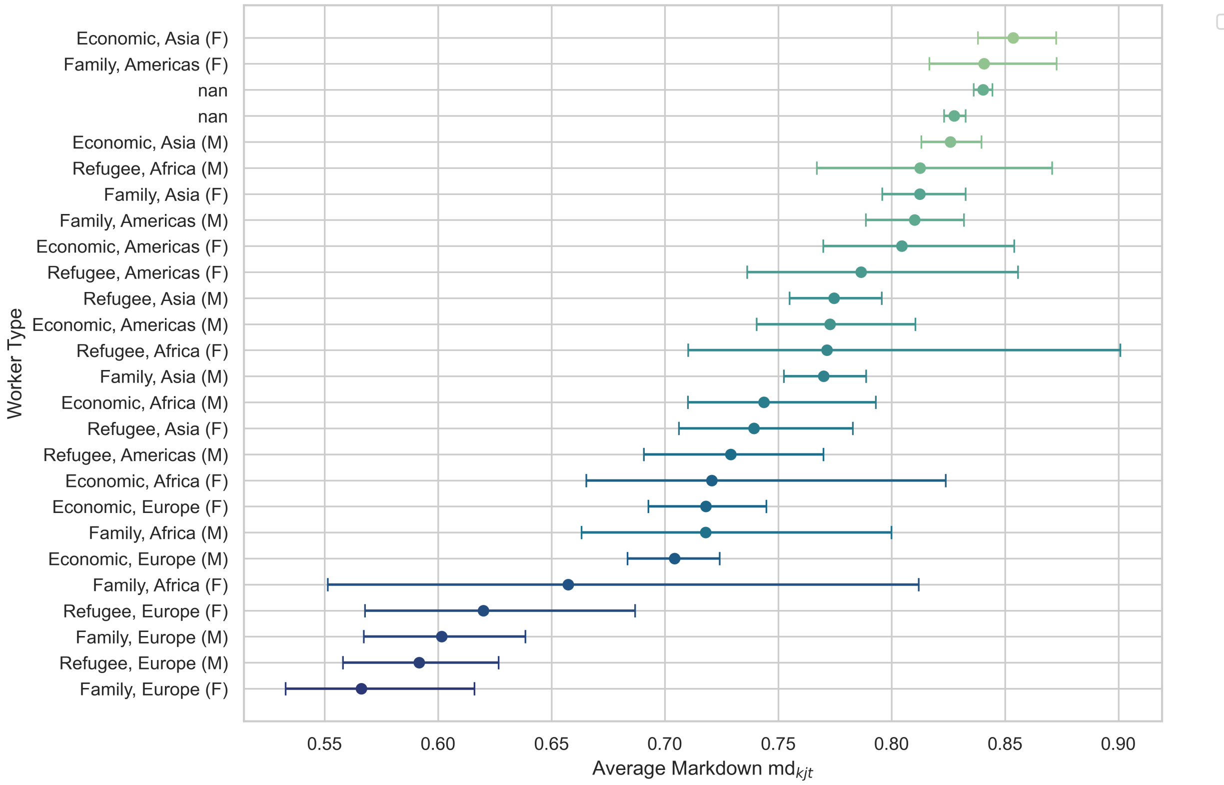
Notes: This figure presents median estimates of the between-firm productivity parameters labor demand parameters. The parameter α_{jt} represents the returns to scale, and the parameter $\tilde{\theta}_{jt}$ represents total factor productivity (TFP). 95% bootstrap confidence intervals (Hall, 1992) are reported. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A4: Heterogeneity in Labor-Supply Elasticities by k-Group



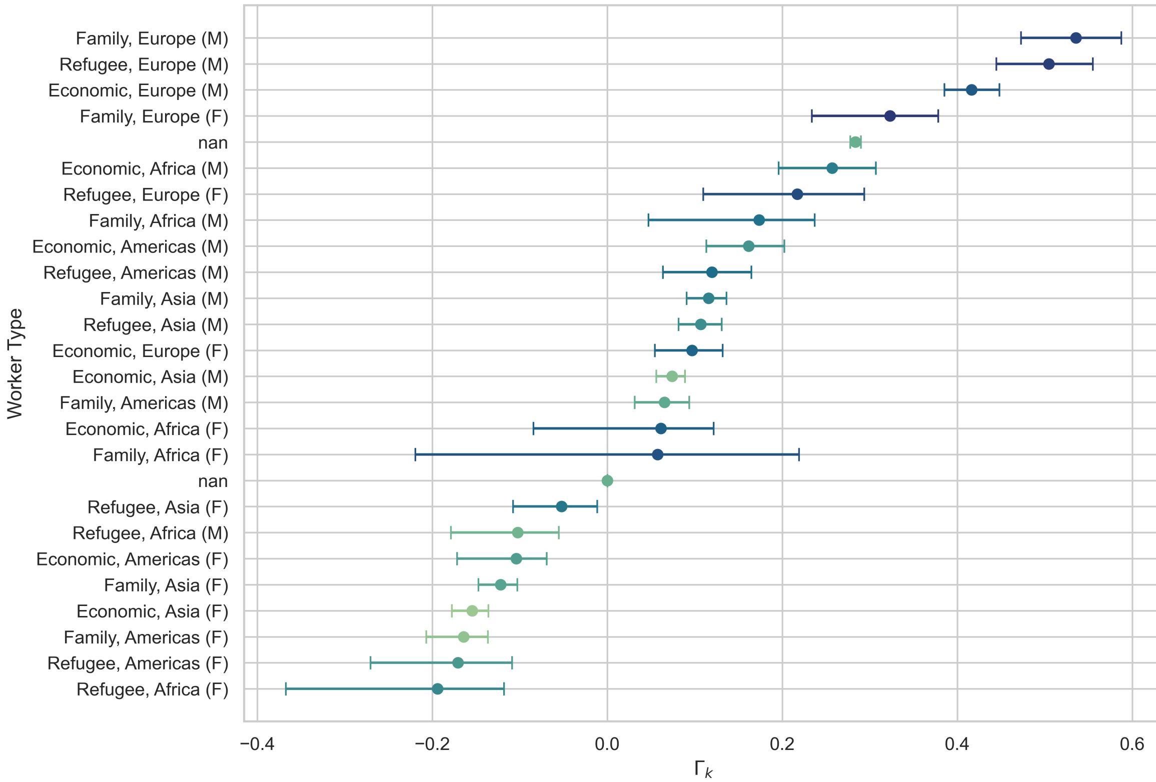
Notes: This figure presents the main estimates of labor-supply elasticities for each k-group. "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's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

Figure A5: Heterogeneity in Wage Markdowns by k-Group



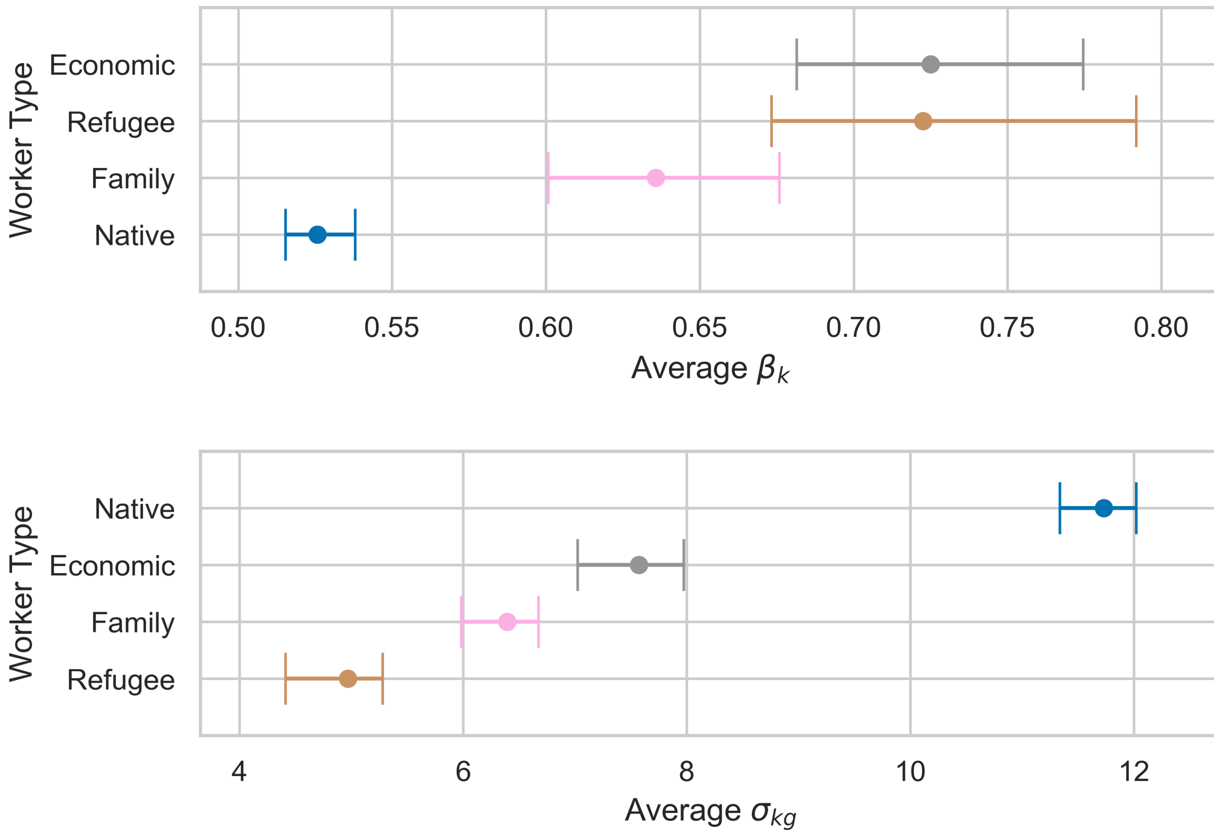
Notes: This figure presents the main estimates of wage markdowns for each k-group. "Average" refers to the employment-weighted average in the data (see Section 2.4). Markdowns are defined as the ratio of the wage to the marginal revenue product of labor (MRPL). According to the first-order condition (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 9). 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



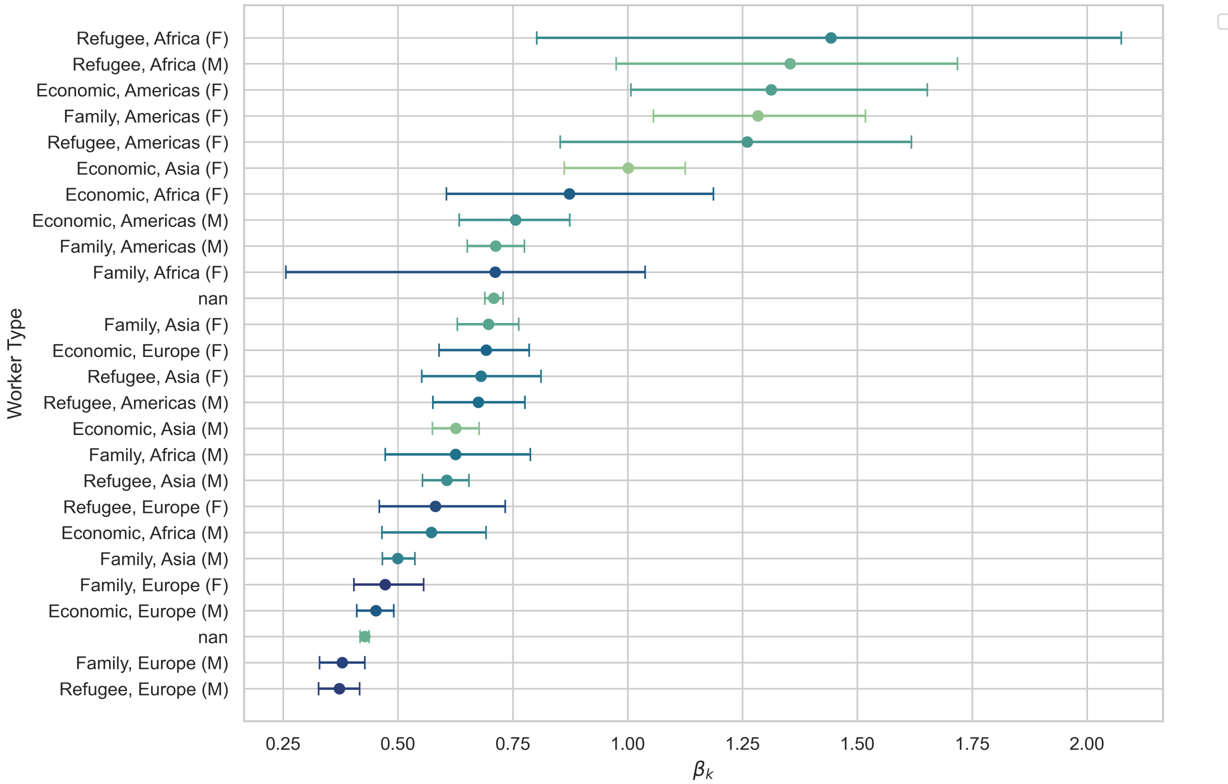
Notes: This figure presents the main estimates of worker skill (Γ_k) for each k-group, obtained from the estimation of equation 30. Ordinary Least Squares (OLS) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A7: Labor-supply parameters by immigration category



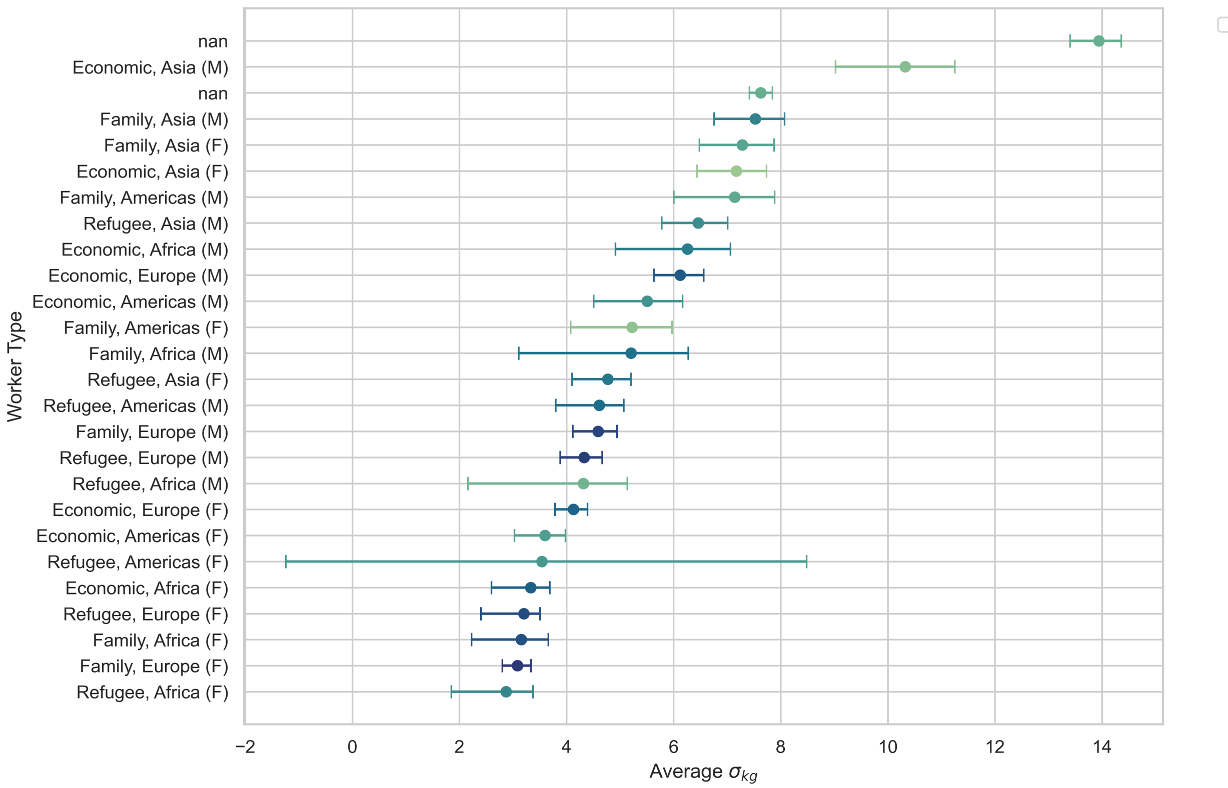
Notes: This figure presents the average estimates of the labor supply parameters for native-born workers and three subgroups of immigrants: economic class, family class, and refugees. The top panel shows estimates of β_k, while the bottom panel shows estimates of σ_{kg}. The parameter β_k represents the marginal utility of the wage in the utility function (see equation 1). The parameter σ_{kg} is the "nest parameter," which is related to the correlation of 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 A8: Estimates of β_k by k-group



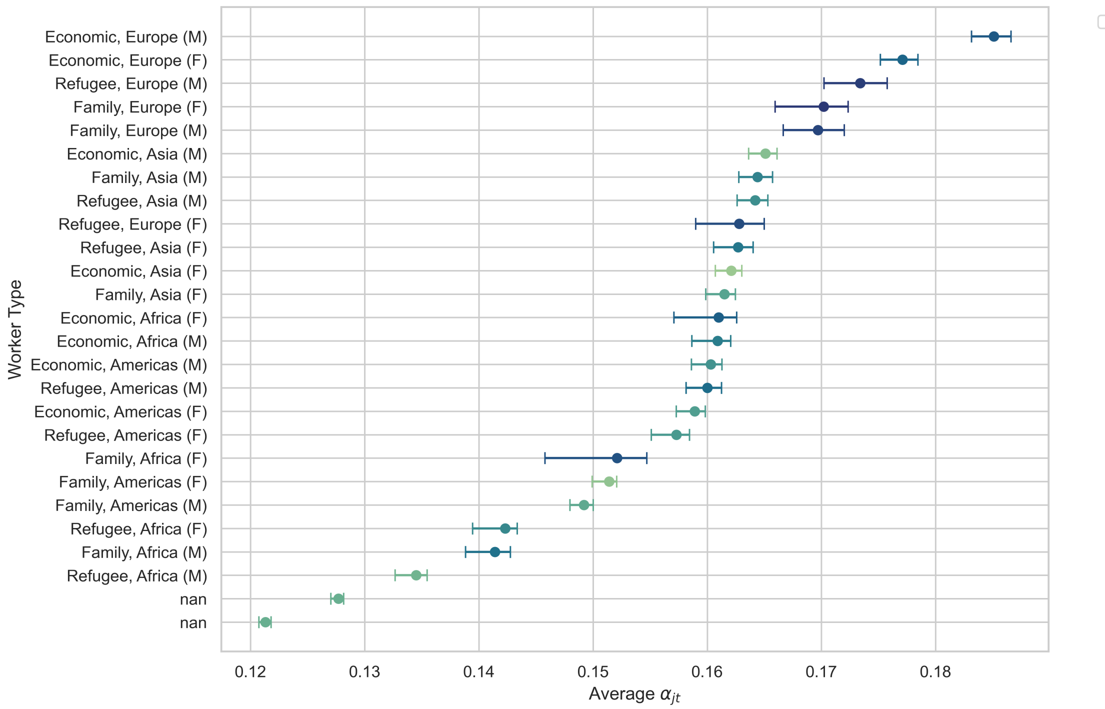
Notes: This figure shows the estimates of β_k. The parameter β_k is the marginal utility of the wage in the utility function (see equation 1). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee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

Figure A9: Estimates of σ_{kg} by k-group



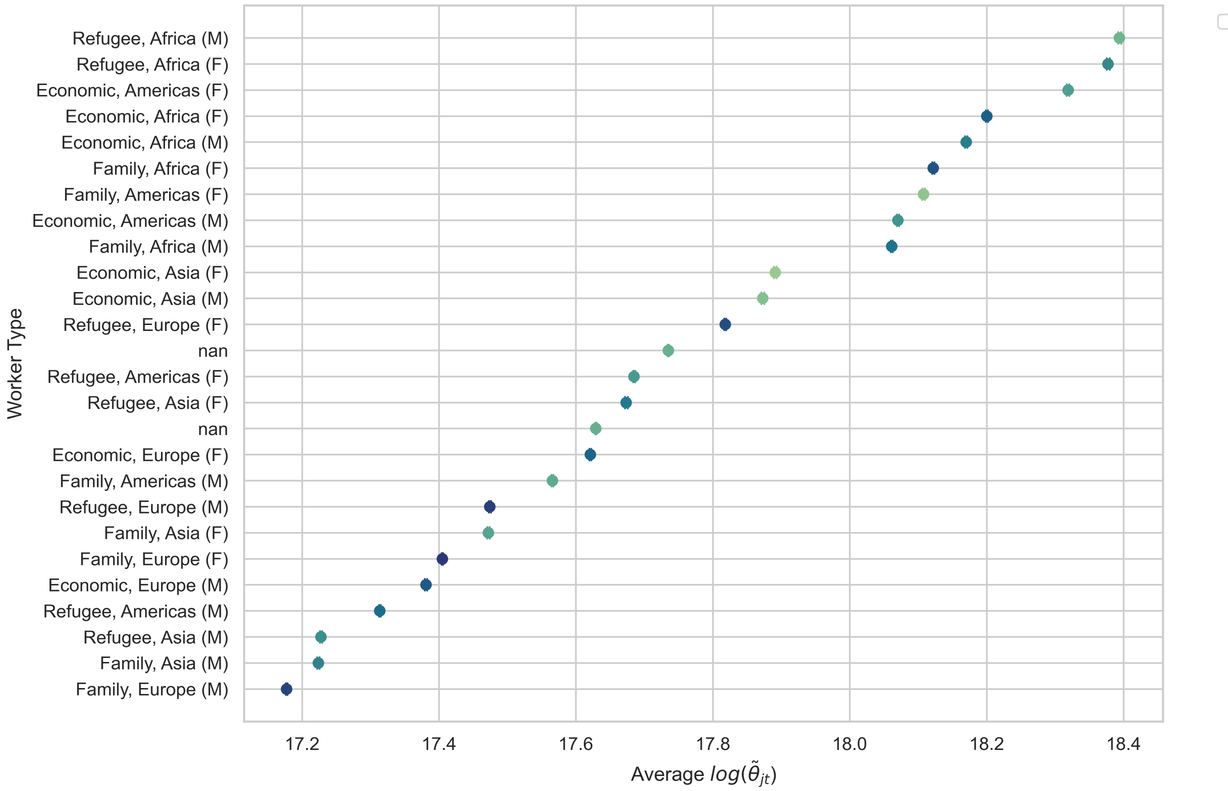
Notes: This table shows the estimates of the average σ_{kg} for each k-group. The parameter σ_{kg} is the "nest parameter" that is related to the correlation of the idiosyncratic preferences (see section 2.2). "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental 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 A10: Estimates of average returns to scale by k-group



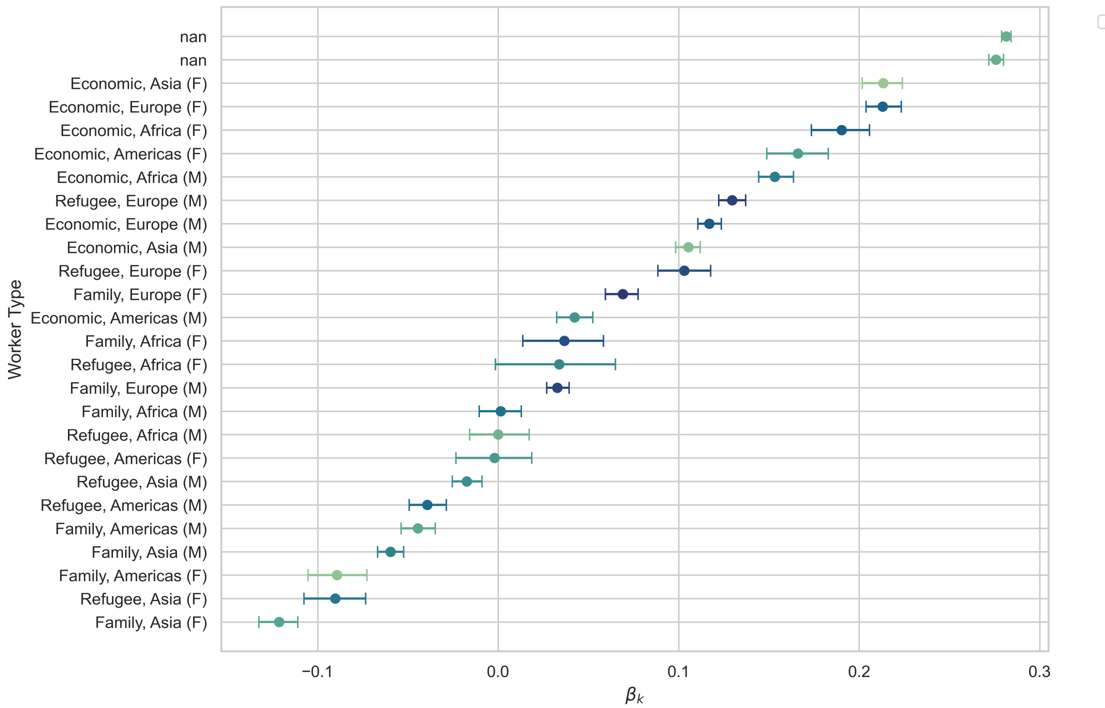
Notes: This figure shows the estimates of the average α_{jt} for each k-group. The parameter α_{jt} captures the returns to scale in the production function (see equation 7). "Average" refers to the employment-weighted average in the data (see Section 2.4). Instrumental variables (IV) estimates are reported, with 95% bootstrap confidence intervals (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

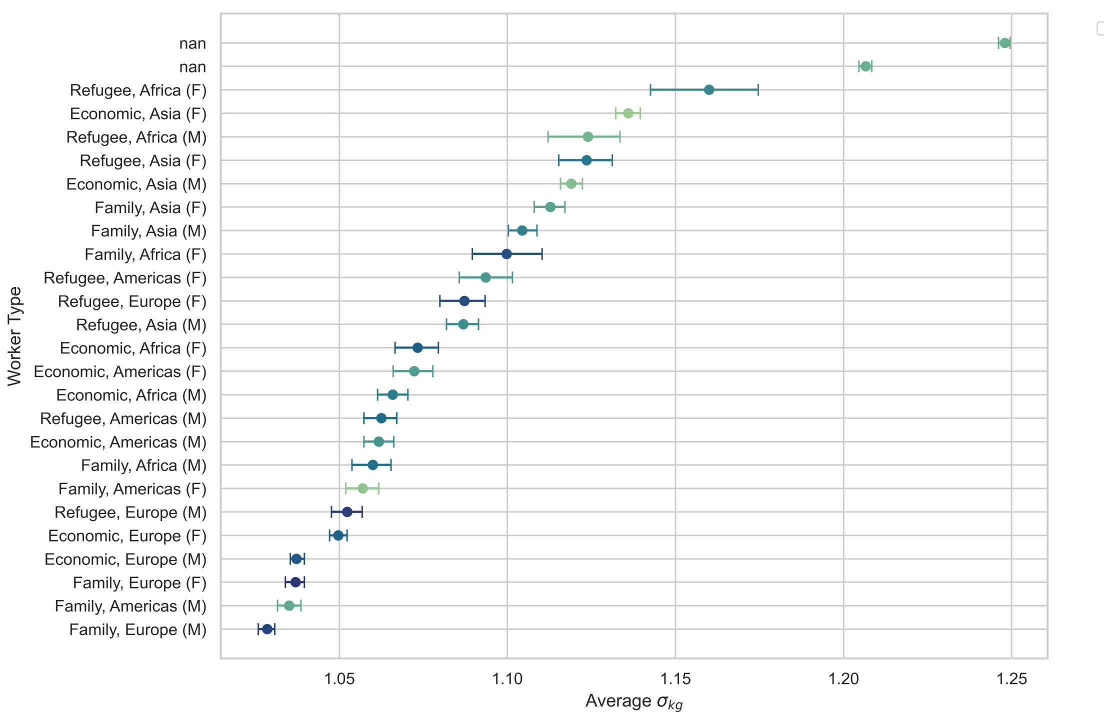
Figure A11: Estimates of average TFP by k-group



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 7). "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).

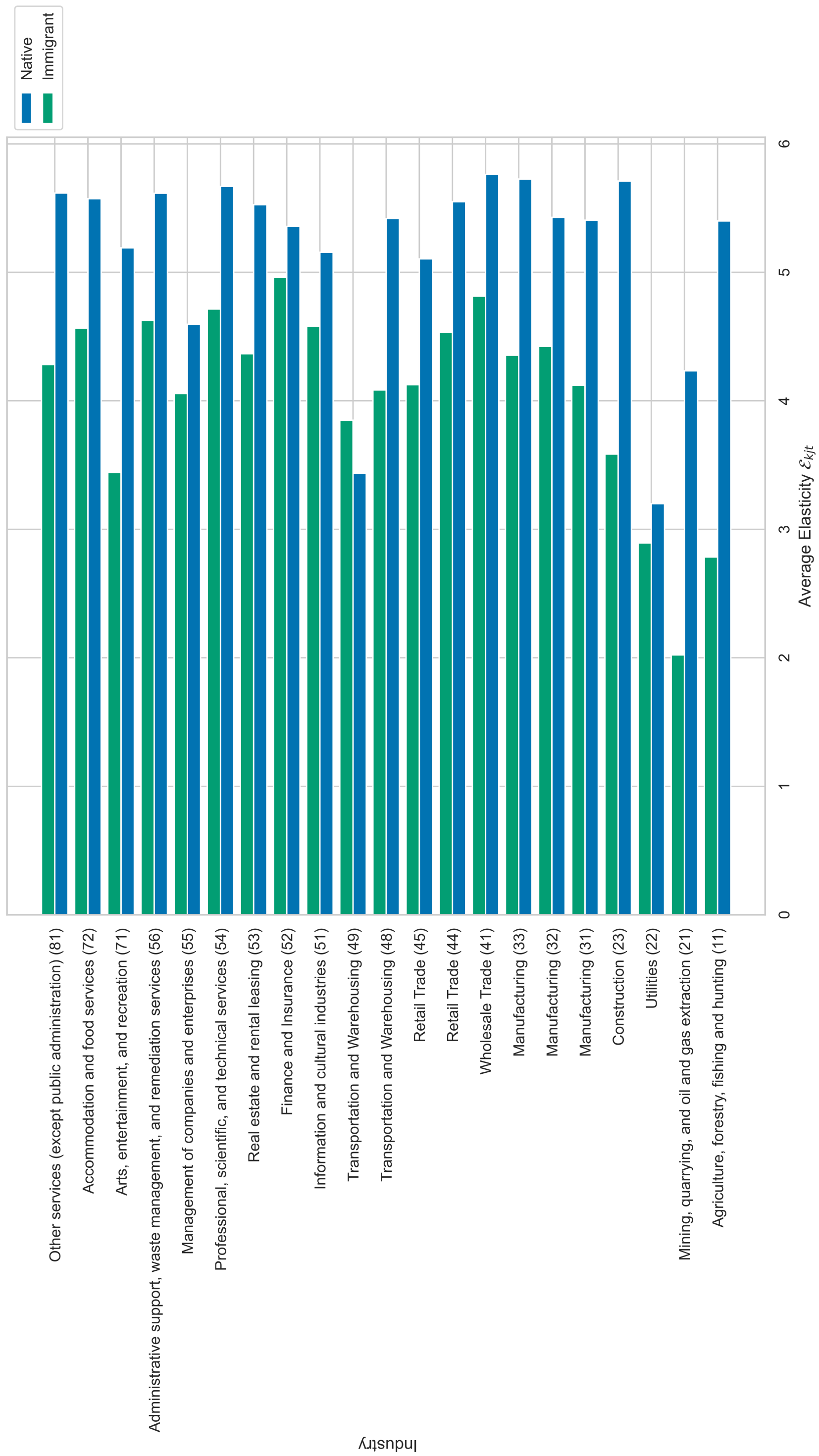
Figure A12: OLS estimates of labor-supply primitives by k-group





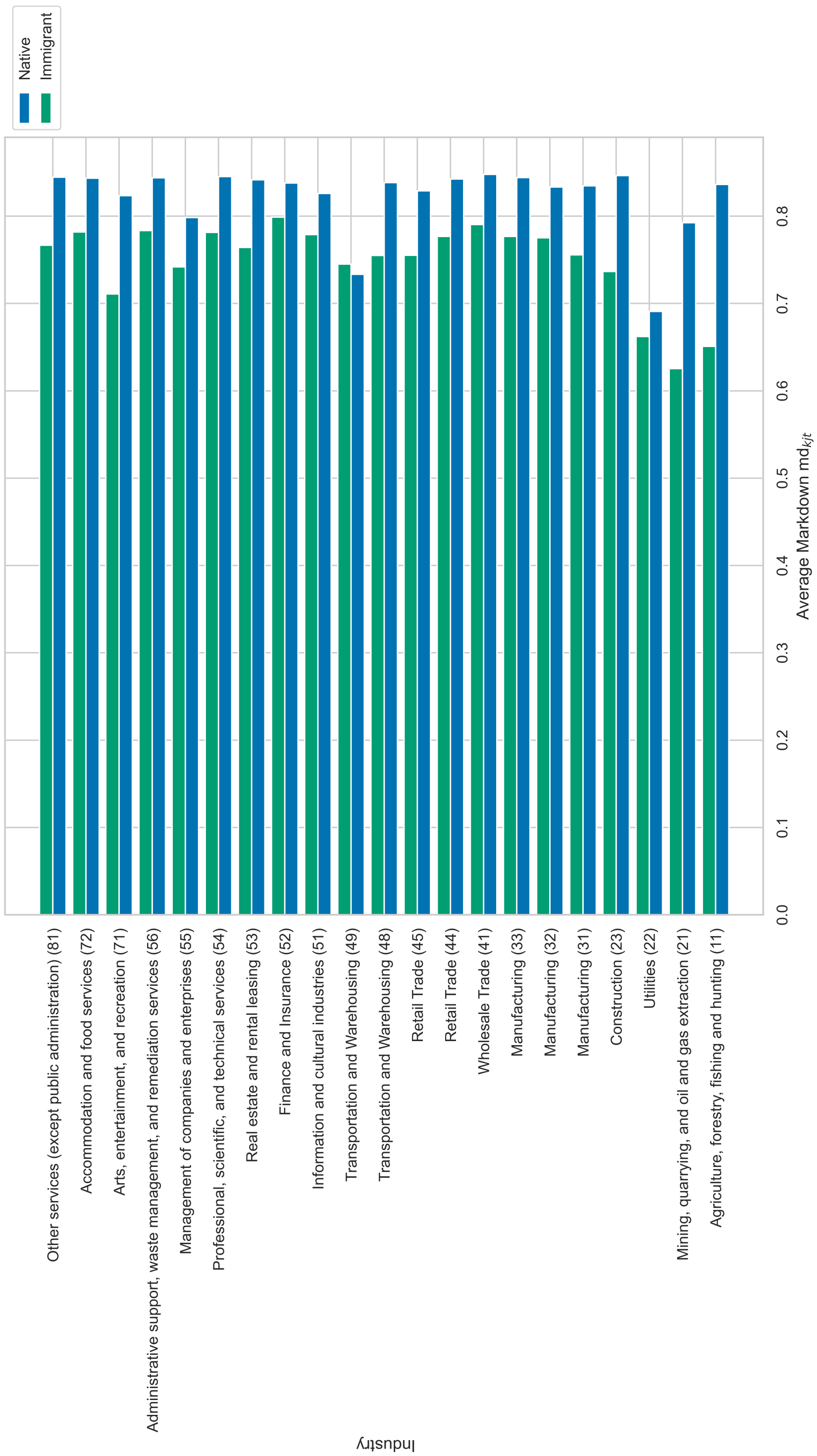
Notes: This figure presents the OLS estimates of the labor-supply parameters β_k and σ_{kg}. 95% bootstrap confidence intervals are reported (Hall, 1992). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A13: Average labor-supply elasticity by industry



Notes: This figure presents the average estimates of labor-supply elasticities across industries (2-digit NAICS). "Average" refers to the employment-weighted average in the data (see Section 2.4). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A14: Average wage markdown by industry



Notes: This figure presents the average estimates of wage markdowns across industries (2-digit NAICS). "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 $\mathcal{E}_{kjt}$ is the labor-supply elasticity (see equation 9). *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

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

$k-$ group	β_k	σ_{k1}	σ_{k2}	σ_{k3}	σ_{k4}
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 12. *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 × Cases		0.007
		(0.103)
Observations	520	520
R-squared	0.01	0.022

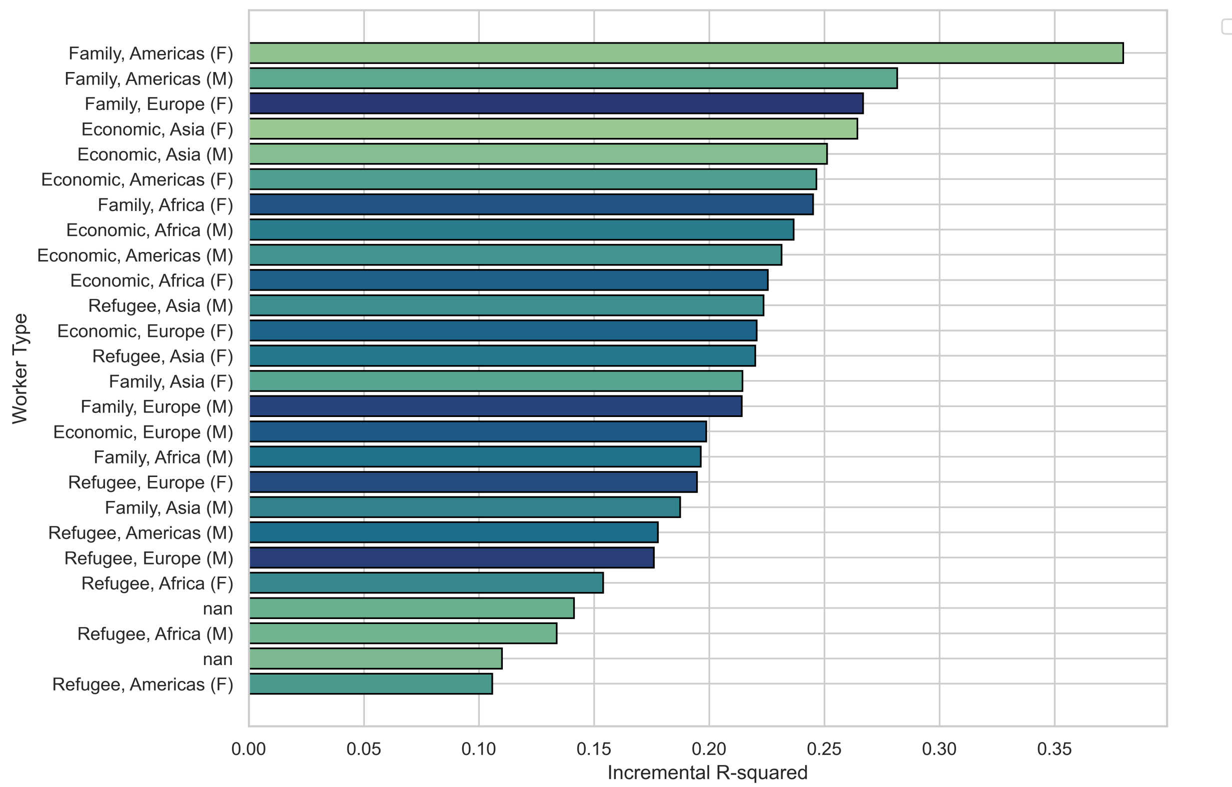
This table presents results from the estimation of equation 27. The dependent variable is $\hat{\psi}^{u}_{kn}$, which are the estimated industry fixed effects from the regression of vertical amenities on firm characteristics (see equation 26). The dependent variable "cases" refers to the cases of illness or injury per 100,000 people. Column (1) shows the simple linear regression of equation 27. 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

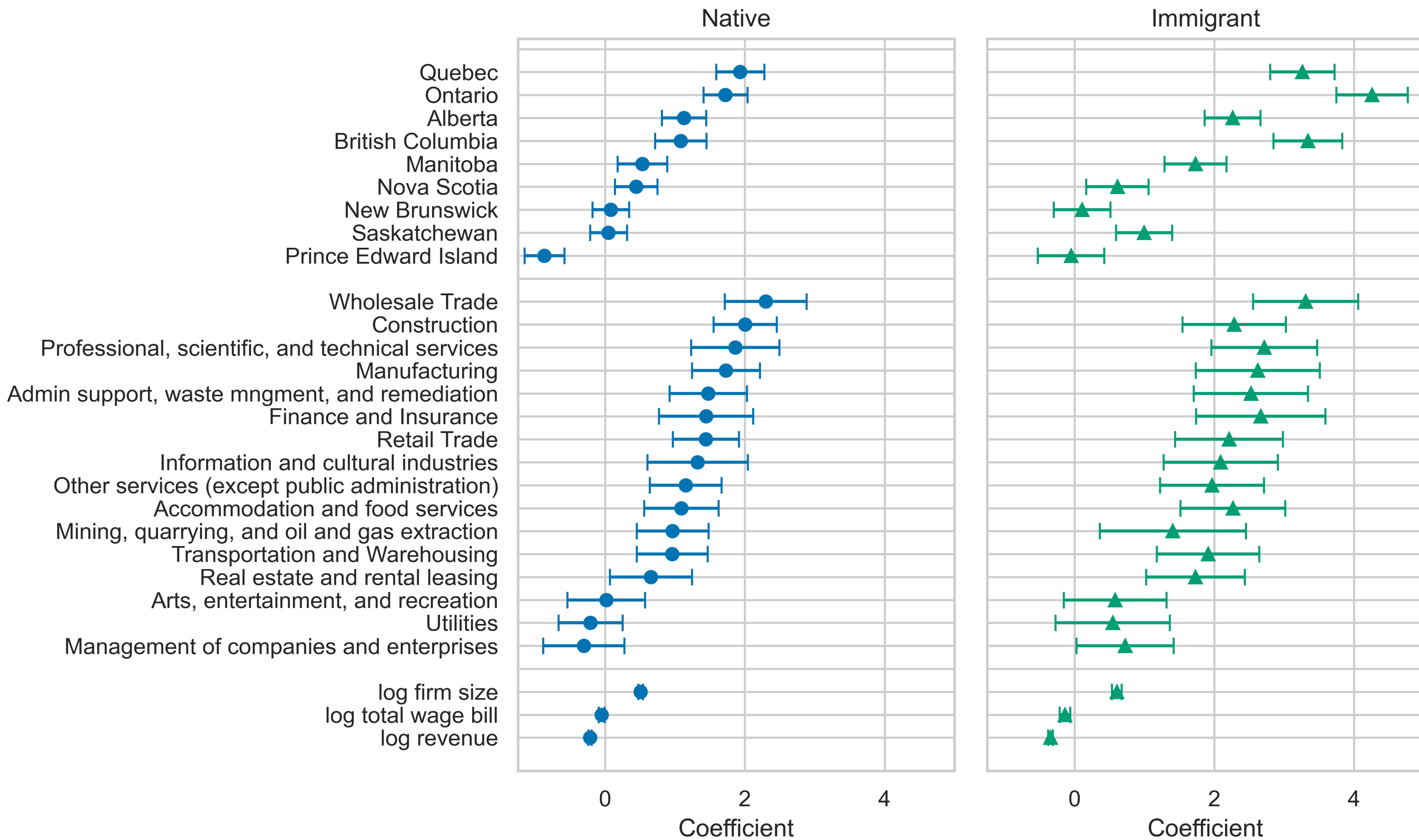
This table presents results from the estimation of equation 30. The dependent variable "Γ_{kt} refers to the worker-type by year fixed effects obtained from the estimation of equation 29. The right-hand side variables are averages of productivity-related variables (education, experience, and language 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)

Figure A15: Incremental R-squared Analyses (Provinces)



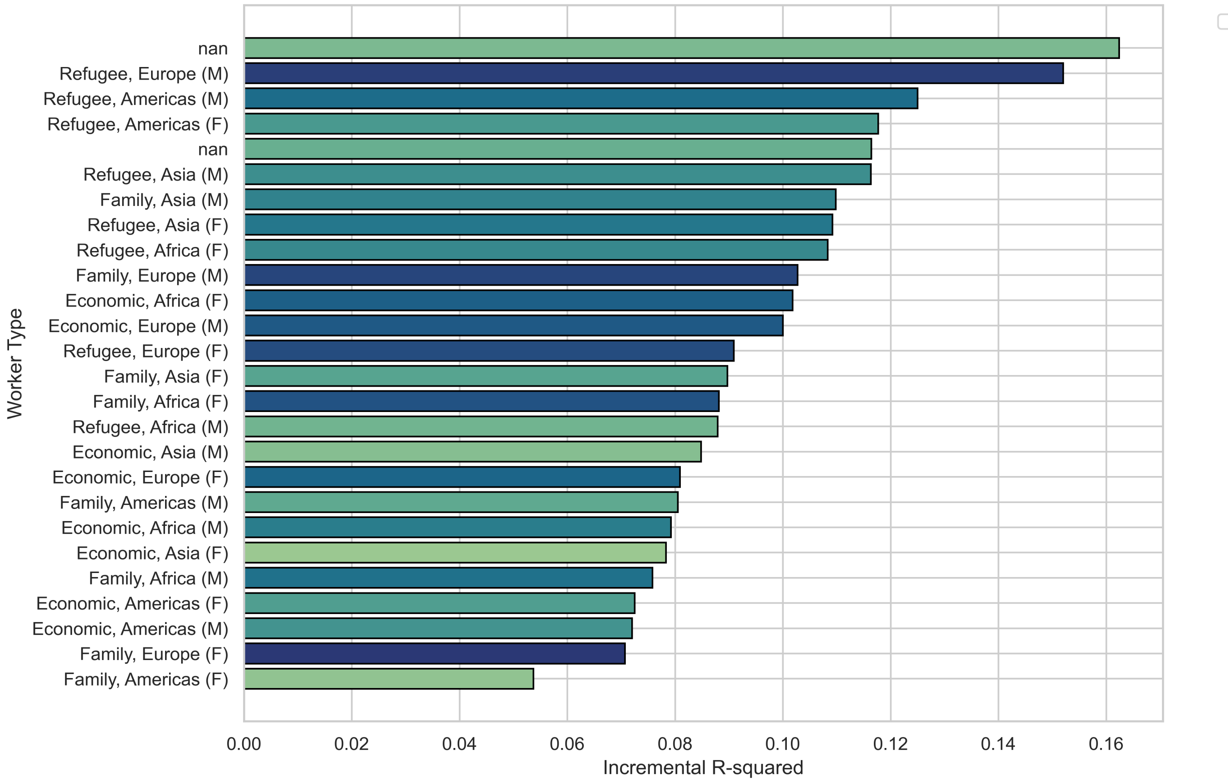
Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with deterministic preferences for amenities. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate equation 26 with all covariates 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 A16: Observed Characteristics Correlated with Deterministic Preferences for Amenities



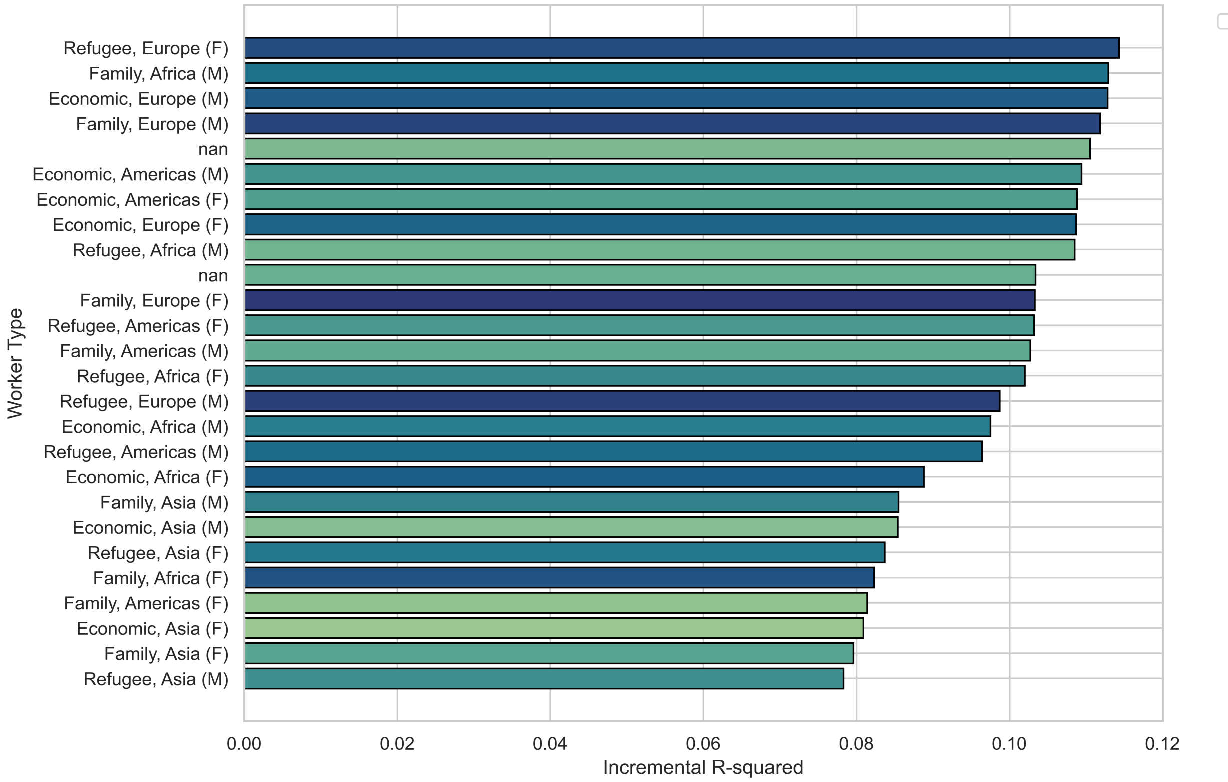
Notes: This figure presents the results from the estimation of equation 26. Standard errors are clustered at the local labor market (CMA × industry) level. *Source:* Author's calculations using the Canadian Employer-Employee Dynamics Database (CEEDD).

Figure A17: Incremental R-squared Analyses (Industries)



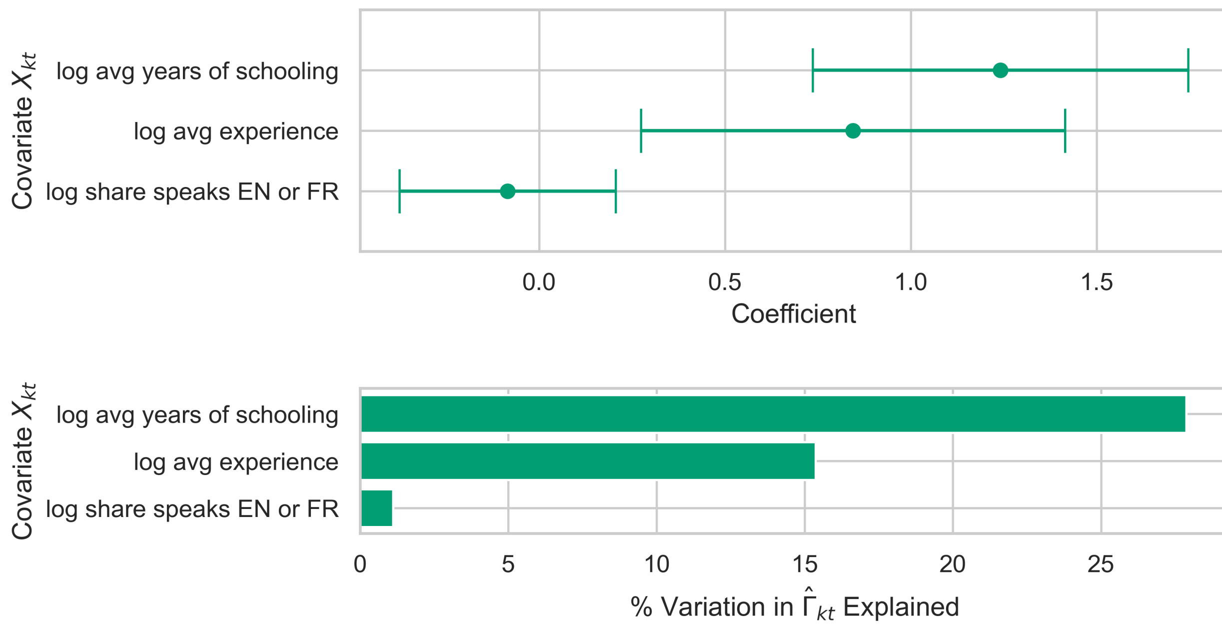
Notes: This figure presents the results from the incremental R-squared analyses that investigate factors correlated with deterministic preferences for amenities. These results are obtained using the following procedure, conducted separately for each k-group. First, I estimate equation 26 with all covariates 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 A18: 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 26 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).

Figure A19: Observed Characteristics Correlated with Model-based Estimates of Worker Skill



Notes: Native-born workers are excluded from this analysis because and language ability are only available for immigrants in the data. In the regression (top panel), standard errors clustered at the k-type level. *Source:* Author's calculations using 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 30 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 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:

$$\log(\hat{\gamma}_{kjt}) = \Gamma_{kt} + \psi_{jt} + e^{\gamma}_{kjt}, \tag{29}$$

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:

$$\hat{\Gamma}_{kt} = \beta^{\gamma}_0 + X'_{kt}\beta^{\gamma}_1 + \nu^{\gamma}_{kt}, \tag{30}$$

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 30 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.