Networks, Sorting, and the Productivity Implications of Immigrant Assimilation [*]

***Preliminary draft for submission to NBER Labor Studies Program Meeting ***[†]

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January 23, 2025

Abstract

Earnings for new immigrants are substantially lower than comparable natives but converge with time in the host country. This paper argues that this phenomenon of wage assimilation is a product of (i) lower initial human capital and (ii) labor market barriers that generate inefficient sorting of immigrant labor. Using matched employer-employee data on the universe of workers and firms in Canada linked with detailed immigrant landing surveys, I present novel differences between immigrants and natives in terms of firm types, labor market dynamics, and the use of labor market networks. Using this analysis, I develop and estimate a general equilibrium model of the labor market featuring two-sided heterogeneity, sorting, and networks. In the model, immigrants land in the host country facing unique labor market barriers and assimilate over time. Networks serve to transmit job information, and I show theoretically and quantitatively that the segregation of networks by origin amplifies between-group wage inequality by giving some groups preferential access to job information. Preliminary results suggest there are substantial aggregate productivity implications from these barriers.

JEL classification numbers: J, E, L
Keywords: Immigration, sorting, wage inequality, search.

[*]I gratefully acknowledge financial support from the Social Sciences and Humanitarian Research Council.

[†]Please note that this project utilizes confidential Canadian micro-data. Results have yet to be formally disclosed. Therefore, all empirical analysis in this draft is based on simulated data from the model and is intended for illustrative purposes only.

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1 Introduction

To what extent are immigrant workers able to productively contribute in the host economy? A robust empirical literature documents that immigrant workers initially experience substantial earnings gaps relative to native workers that gradually narrow over time—a process referred to as 'assimilation'. This is commonly attributed to human capital differences: immigrants may have acquired less human capital in their source country (e.g., due to weaker institutions) or face challenges in transferring their skills to the new labor market. On this view, immigrant assimilation is a product of lower initial productivity followed by human capital investment (Borjas (2015); Adda *et al.* (2022); Albert *et al.* (2021)).

However, this explanation alone abstracts from the role of the firm. There is by now a consensus that differences in sorting across firms account for a non-trivial portion of wage inequality, both in general and between worker groups (Card *et al.* (2013); Card *et al.* (2016); Song *et al.* (2019); Gerard *et al.* (2021)). Barriers such as language difficulties, occupational regulations, and discrimination may limit efficient allocation of immigrant labor compared to native workers (Oreopoulos (2011); Imai *et al.* (2019); Brücker *et al.* (2021)). Moreover, and as I argue in this paper, the segregation of labor market networks by ethnicity may further widen between-group differences in the types of jobs workers have access to.

Disentangling the role of these two explanations—differences in human capital versus differences in allocation across firms—is critical for assessing the productivity implications of immigrant-native wage inequality and for crafting immigrant integration policies. However, this distinction is difficult to make empirically. Worker ability is unobserved, and differences in the types of firms that immigrants and natives are employed at could equally be due to barriers that distort the allocation of immigrant labor or the optimal sorting of workers with different levels of ability.

This paper aims to quantify the productivity losses caused by immigrant labor market barriers and understand the contributions of allocational barriers versus human capital differences for immigrant wage inequality and the assimilation process. Using matched employer-employee data on the universe of workers and firms in Canada from 2001-2019, linked with unique immigrant landing data, I begin by carefully documenting immigrant assimilation patterns. I find that immigrants have substantially lower monthly earnings and that this gap closes with time in Canada. I also find that new immigrants are employed at firms that are substantially smaller, lower paying and less productive, and sort into better firms over time. I then document novel differences between immigrants and natives in terms of labor market dynamics and argue that these are consistent with immigrants facing barriers to efficient sorting. Finally, I document strong 'ethnic hiring patterns', in that immigrants gravitate towards firms with a higher share of incumbent workers from the same

country of origin.[1] These patterns do not appear to be driven by immigrants sorting into certain types of firms, making them difficult to rationalize using existing labor market models. My models captures these patterns by allowing for ethnically segregated labor market networks that serve as a conduit of job information.

Using these patterns, I develop and estimate a model of the labor market featuring search frictions, two-sided heterogeneity, sorting, and labor market networks. I show theoretically that the segregation of labor market networks by ethnicity amplifies wage inequality by lowering the total job finding rate and shifting downwards the job distribution for disadvantaged groups. Labor market networks therefore serve as one micro-foundation for the immigrant-native wage gap and subsequent wage assimilation by further widening the gap in sorting between equally productive native and immigrant workers. I identify the role of allocational barriers from labor market dynamics and identify the role of networks using ethnic hiring patterns. The remainder of wage assimilation is driven by human capital accumulation. Using the estimated model, I plan on conducting a series of counterfactuals to evaluate the implications of different types of immigrant integration policies, such as job search training, landing support, and equal pay policies.

The outline of the paper is as follows. In Section 2 I describe the data and comprehensively document differences in labor market outcomes and dynamics between immigrant and native workers. In Section 3 I develop an equilibrium model of the labor market. In Section 4 I discuss how the model relates to the empirical findings, how the model parameters are identified, and estimation. In Section 5 I use the estimated model to quantify the productivity implications of immigrant labor market barriers and the role of networks and sorting, and conduct of number of counterfactuals that highlight effective avenues for immigrant integration policy. Section 6 concludes.

My paper differs from previous work in two respects. First, these models do not feature heterogeneous firms, which is necessary for studying sorting. Second, in almost all of the aforementioned work there is a single network where job information is transmitted. I build on this work by embedding labor market networks into a search model with two-sided heterogeneity and then introducing a micro-foundation for between-group wage inequality that arises when workers from different groups have access to different networks. Since networks are often formed on the basis of ethnicity, the personal contacts that immigrants rely on for job information will themselves face larger barriers to finding employment than the average native. As a result, their contacts are less likely to be employed in high productivity firms, and it is these firms who disproportionately use referrals in hiring. This network structure of job finding therefore amplifies labor market inequality between immigrants and natives since the aggregate state of ones contacts effects the arrival rate and distri-

[1] Gyetvay and Keita (2024) finds similar evidence in Germany.

bution of job opportunities.[2] This amplification also cuts the other way: Policies that improve one immigrants' outcomes have spillover effects on other workers through their network, making the incorporation of networks important for quantitative analysis of immigration policy.

Secondly, my model builds on random search models with two-sided heterogeneity, which are frequently used to study wage inequality and the allocation of labor (Cahuc *et al.* (2006); Lise *et al.* (2016)). Because of growing evidence that workers search intensity is not inelastic (see Faberman *et al.* (2022)), I follow Bagger and Lentz (2019) and allow for endogenous search intensity that depends on the workers type and state. As in their context, endogenous search intensity is important for explaining empirical duration dependence patterns. However, it may also have important implications for quantifying the effects of immigration policies, since even policies that do not directly effect immigrants search technology may change their *incentives* to search. As in Morchio and Moser (2024) I also allow for distinct worker groups in order to analyze between-group labor market gaps. However, none of these models allow for job finding through personal networks. My main contribution relative to these models is to show that networks can be parsimoniously embedded in a way that preserves the functional structure of the fixed point problem, thus retaining tractability and uniqueness and existence properties.

Finally, my work relates to a large literature trying to understand immigrant assimilation. Empirical analysis finds that when immigrants land there are substantial differences in wages relative to observationally similar native workers, with a significant share stemming from differences in firm pay, and that this tends to close over time as immigrants assimilate to the host country (Dostie *et al.* (2023); Arellano-Bover and San (2023)). Other work identifies certain barriers or reasons explaining why immigrants have these initial disadvantages, such as occupational barriers, language barriers, and discrimination (Oreopoulos (2011); Imai *et al.* (2019); Brücker *et al.* (2021); Foged *et al.* (2024)). I contribute to this literature in two ways: First, I offer a novel empirical description of how immigrants navigate the labor market relative to native workers. This rich comparison of labor market dynamics helps illuminate the underlying sources leading to differences in allocation across firms. Secondly, I develop a search model with parameters that directly map to the empirical analysis and then ask which types of integration policies are the most promising for improving the integration of immigrants.

My work compliments other structural models looking at immigrant assimilation (Adda *et al.* (2022); Albert *et al.* (2021)). Like these models, I allow for the fact that not all of an immigrants human capital is immediately portable across countries, and that they must accumulate host-country specific human capital, resulting in wage assimilation. However, these models have no notion of how workers sort and form employment relationships. I allow for the possibility that there are fea-

[2] A similar intuition of network-induced wage inequality is found in Fontaine (2008).

tures of the labor market that affect immigrant productivity through sorting across jobs rather than just through their individual human capital. In contemporaneous work, Birinci *et al.* (2021) also formally model barriers to immigrant labor allocation in the context of the United States. They employ a static one-period Roy model and focus on barriers across occupations, finding that such barriers lead to significant output losses. These barriers are modeled as macro "wedges" in the tradition of Restuccia and Rogerson (2008) and Hsieh *et al.* (2019). I instead focus on allocation across *firms* in a dynamic search model where differences in the allocation of immigrants is micro-founded by differences in human capital-induced sorting, search fictions and networks that induce differential access to job information in order to study immigrant assimilation.

The economic assimilation of immigrants will be of growing importance to policy makers in developed countries as immigration rates reach all-time highs and are predicted to continue this way into the future. A fundamental policy challenge for these countries is how to maximize the economic contribution of immigrant workers. This is a challenge because the data suggest immigrants face unique barriers that hinder their integration into the labor market, rendering them temporarily less productive than they otherwise could be and more poorly allocated across firms. It is the hope that this work can not only quantify how important these barriers are but also offer some helpful guidance into what types of integration policies will be effective.

2 Empirical findings on immigrants in the labor market

In this section, I explore salient differences between immigrants and natives in terms of earnings, labor market dynamics, and co-ethnic hiring patterns that will motivate and discipline the model described in the following section. Since the model abstracts from aggregate fluctuations and life cycle components, unless otherwise stated all comparisons are conditional on age, year and region fixed effects.

2.1 Data and Background of Immigration in Canada

The primary data source is the Business-Employee Administrative Microdata (BEAM), which is matched employer-employee Canadian administrative data covering the universe of workers and firms in Canada from 2001-2019. This data links the workers Record of Employment (T4ROE) with their individual tax form and their employers tax records. The T4ROE allows me to observe employment histories for each worker including firm identifiers, annual employee income at each job (T4) and start and end dates at monthly frequencies which I use to calculate labor market

transition statistics and a measure of monthly earnings at each job.[3] All income variables are deflated to 2015 Canadian dollars.

This dataset is then linked to Canada's Longitudinal Immigration Database (IMDB), which is detailed immigration data allowing me to identify immigrant workers from the tax data along with their country of origin, their landing year (date of obtaining permanent residency), history of temporary permits prior to landing, education and language proficiency upon arrival, intended occupation, and channel of entry. The IMDB covers all immigrants who landed since 1982. The comprehensive coverage of high-quality matched administrative tax data merged with detailed characteristics of every immigrant worker is noteworthy as most previous literature on immigrant assimilation relies on observing how the wages of a (synthetic) cohort of immigrants evolves over a series of decennial cross-sections, or else has a short time horizon and less coverage.

The vast majority of immigrant workers in Canada are "permanent residents" (PRs). These are workers who migrated from abroad and have been granted permanent access to live and work in Canada. Permanent residents may enter through three main channels: Economic, family, and refugee/humanitarian. Immigrants seeking to enter Canada through the Economic channel are ranked according to a points-based system that takes into account their experience, language proficiency, education, age, and other factors that are thought to affect their potential success in Canada. Individuals with scores above a threshold are then invited to apply for permanent residency. Immigrants entering through the family channel are sponsored by an existing Citizen or PR, and are most often the spouse or child of an economic immigrant. The remainder of PRs enter as a refugee or on other humanitarian grounds. Importantly, permanent residents are not tied to a single firm, and indeed many land unemployed and then search for work. This is unlike the H1-B program in the United States, where permission to work is tied to a sponsoring firm. The remainder of immigrants are Temporary Foreign Workers (TFWs). These are individuals who are granted permission to live, work, and/or study in Canada temporarily for a pre-specified duration. Often times, individuals first come to Canada as a TFW and obtain PR status later.

[3]The ROE is a mandatory form that employers are required to submit whenever a workers experiences an interruption of earnings, including separations. Conversations with Statistics Canada confirmed that the only legitimate reason for a job spell missing start and end dates is that the job is current. In practice, there appears to be a large number of observations for which a separation occurred but start and end dates are missing (i.e., a Record of Employment was not submitted). These were typically associated with long, consistent employment relationships. For jobs with T4 earnings reported for three or more consecutive years, I assume 12 months worked during interior years and compute monthly earnings as annual earnings divided by 12. For the start and end dates, I assume that monthly earnings in the first year are the same as the second, and the last year the same as the second last, and back out months by dividing annual earnings by imputed monthly earnings. For jobs with two or less consecutive years, I drop those earnings less than $15,000$ in average real annual income and impute 12 months to the remaining. Results based on monthly earnings are comparable to annual earnings and in the appendix I report labor market dynamics using only transitions between non-imputed spells.

I restrict attention to individuals aged 25-65 having a strong attachment to the labor market. In particular, I remove individuals who have two or more consecutive tax years with no reported labor income (T4 slip). Due to the job mobility restrictions inherent with TFWs, I keep only observations for which the individual was a permanent resident. I further define immigrants as those who landed as permanent residents at age 16 or older, and consider those who landed prior to age 16 as native workers.

2.2 Immigrant Assimilation

Documenting immigrant assimilation is more complex than simply taking the average wage gap of recently landed immigrants and comparing it to immigrants who have been in the host labor market for longer time periods. Consider the simple regression,

$$w_{it} = \beta_1 imm_i + \sum_{y=2}^{10} \beta_y \mathbb{I}\{YSL_{it} = y\} + \delta_t + \rho_{r(i,t)} + \alpha_{a(i,t)} + \epsilon_{it} \tag{1}$$

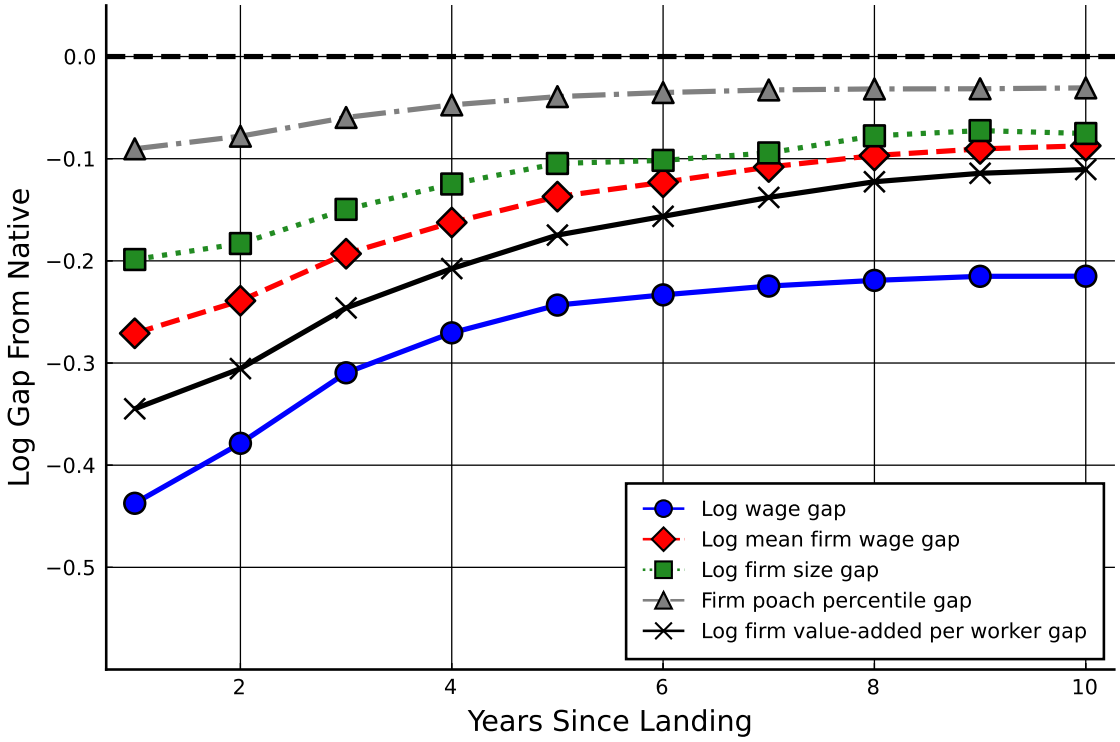
where w_{it} is log wages for individual i at year t, imm_i is an indicator variable equal to one for immigrants, YSL_{it} gives the number of full years the immigrant has been a landed permanent resident, and δ_t, $\rho_{r(i,t)}$, and $\alpha_{a(i,t)}$ are time, region, and age fixed effects. The coefficient β_1 provides the initial immigrant wage gap, and β_y how much that gap has closed y years after landing.

The challenge with interpreting the β_y estimates from equation (1) as wage assimilation is that the set of immigrant workers in the $YSL_{it} = y$ bin are not the same as those in the $YSL_{it} = y'$ bin. There are at least three sources of selection that induce compositional changes across years-since-landing groups: (1) Earlier immigrant cohorts will load more into later years-since-landing bins, and earlier cohorts may be fundamentally different than newer cohorts, (2) selective out-migration, and (3) selective delayed entry into the labor market (Rho and Sanders (2021)). This confounds the wage assimilation estimates from equation (1) with compositional changes, making them difficult to interpret.

The panel nature of my data combined with rich immigrant variables allows me to address and quantify all three of these selection issues. This is unlike most of the literature on immigrant assimilation that uses a series of cross-sections. I run the following regression,

$$w_{it} = \beta_1^{C(i)} cohort_{C(i)} + \beta_1^{R(i)} return_{R(i)} + \beta_1^{D(i)} delay_{D(i)} + \sum_{y=2}^{10} \beta_y^{FE} \mathbb{I}\{YSL_{it} = y\} + \delta_t + \rho_{r(i,t)} + \alpha_{a(i,t)} + \epsilon_{it} \tag{2}$$

Figure 1: Wage and firm type assimilation

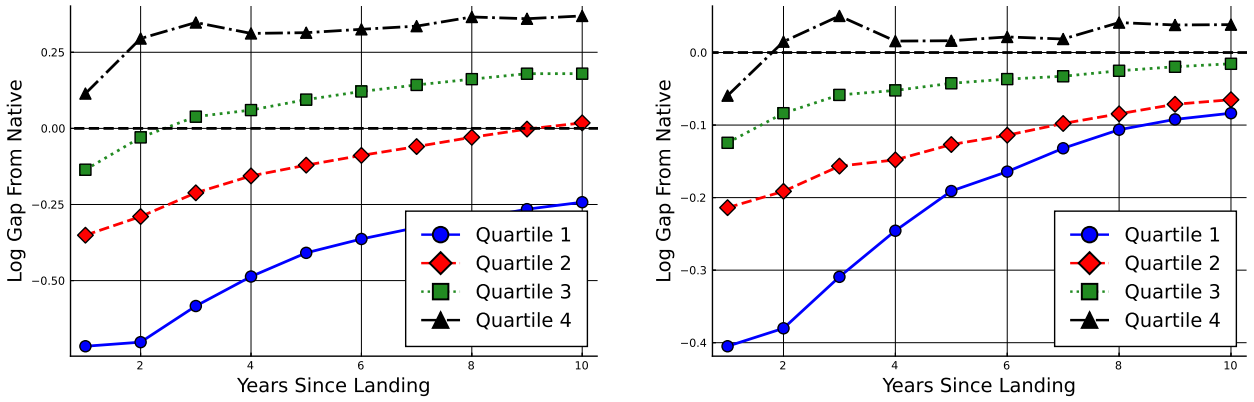


By including fixed effects for landing cohort ($cohort_c$), years between landing year and labor market entry ($delay_d$), and possible return migration $return_{R(i)}$, β_y^{FE} now returns the average wage growth of immigrants relative to natives *within* these immigrant groups. Unlike equation (1), changes in the composition of immigrants no longer loads into β_y, removing confounding composition effects. Since the level of wage differences relative to natives is no longer identified, I set the level such that the average wage gap is equal to the cross-sectional estimate for immigrants with $YSL_{it} = 10$.

The solid blue line in Figure (1) shows that new immigrants make about 45 log points less than native workers of the same age in the same local labor market, decreasing to about half that 10 years after arrival. This substantial gap in earnings followed by gradual convergence has motivated a vast literature on immigrant assimilation and suggests that immigrants may indeed face substantial labor market barriers that have aggregate implications.

The rest of the lines in Figure (1) highlight that there are also substantial gaps in the types of firms that immigrants work at. The red dashed line shows that immigrants work at firms with mean log wages 28 points lower than natives when first arriving and 9 points lower 10 years later. This motivates one of the key emphases of this paper that the *allocation* of immigrants across firms is important, and that immigrants may face other types of barriers (other than simply lower human

Figure 2: Wage and firm type assimilation by initial wage quartile



(a) Log Wage

(b) Mean Firm Log Wage

capital) that affect their ability to allocate efficiently across jobs. Of course, differences in firm types is not direct evidence of immigrant mismatch. Part of the differences in allocation may be optimal sorting due to lower human capital.[4] This motivates the development of a structural model of worker sorting that can disentangle these two explanations. Moreover, in the following subsections I document differences between immigrants and natives in terms of labor market dynamics and job finding patterns that provide more explicit evidence of such allocation barriers.

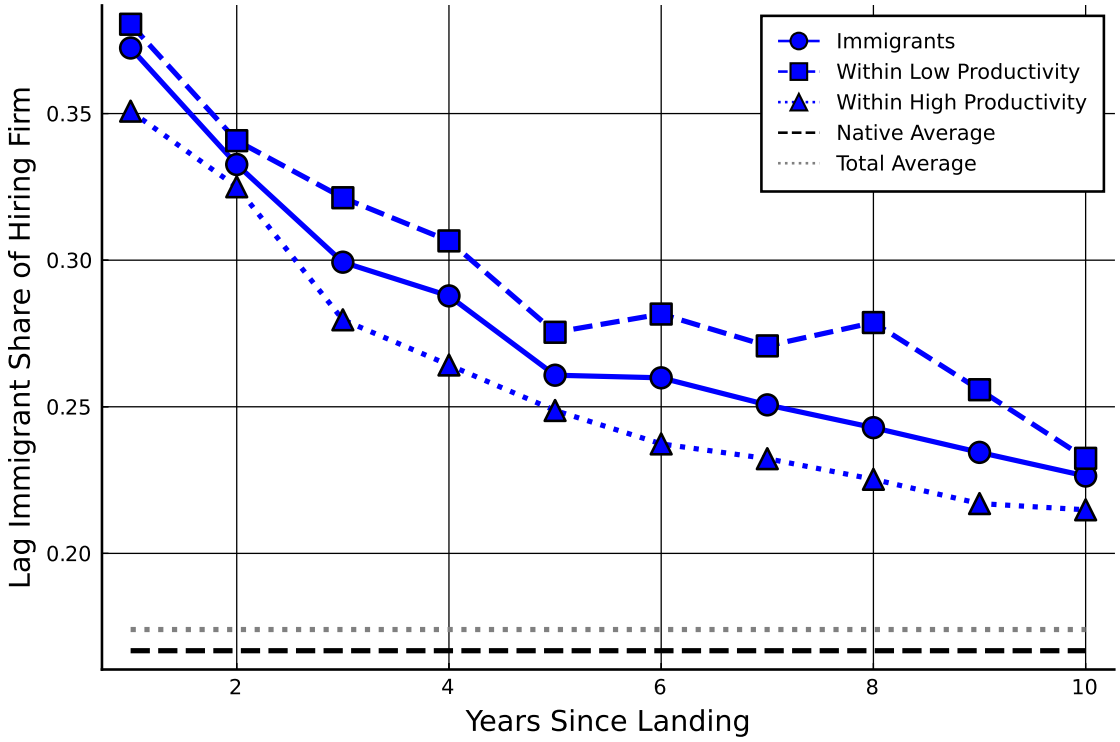
Figure (2) plots wage and firm mean wage assimilation patterns separately by binning workers into quartiles based on their average earnings over the first two years, which I view as a noisy method of differentiating workers by initial productivity. We see that these workers have very different wage and firm type assimilation patterns, suggesting that different types of workers may face different degrees of labor market barriers, and may have different incentives for assimilation. When I go to estimate the model, I will use these patterns to identify the functions governing human capital and allocation barriers.

2.3 Segregated Labor Market Networks

The Longitudinal Survey of Immigrants to Canada surveyed a cohort of new immigrants who landed in Canada between 2001-2002, asking a battery of questions trying to understand how immigrants adapt to the new labor market. For each job held in the first four years after landing, the worker is asked how they found the job. If found through a personal contact the worker is then asked whether that contact was of the same ethnicity. I find that 44% of all immigrant jobs were found through personal contacts and that almost 90% of these contacts were reported as being of the same ethnicity, confirming that networks are a key source of job information and that they are

[4] Gerard *et al.* (2021) found that this can explain a large share of the racial firm sorting gap in Brazil.

Figure 3: Immigrant Share of Firm for New Hires



segregated by ethnicity.

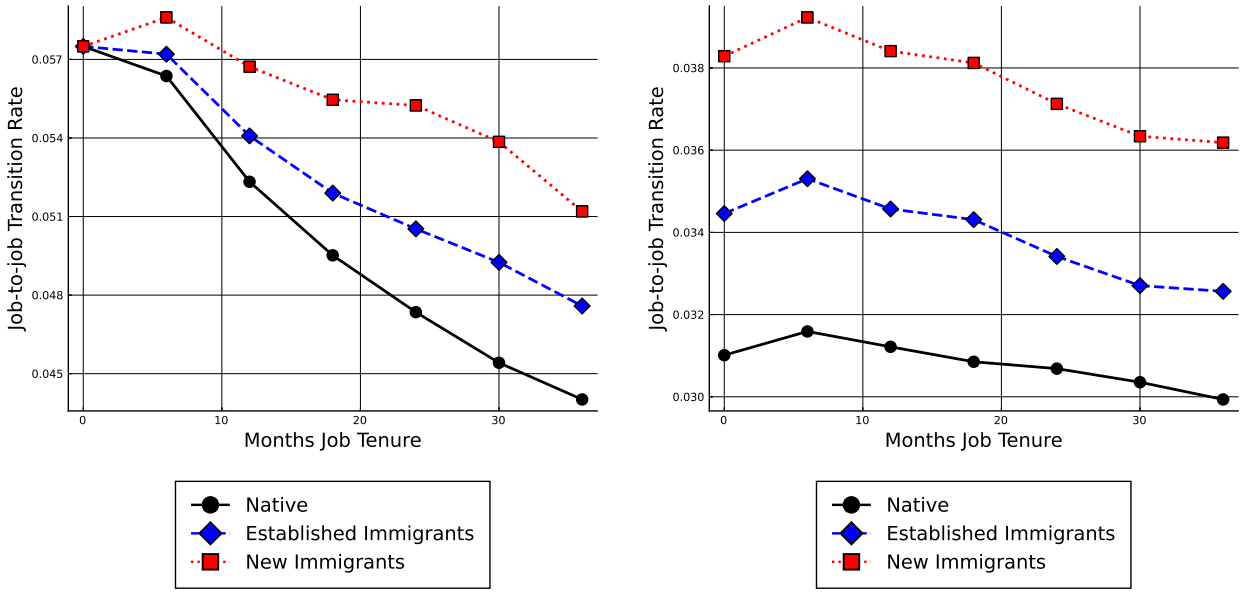
Ethnic-based labor market networks will manifest in the administrative data by affecting job flows and hiring patterns. In particular, we should observe workers gravitating to firms that have a higher share of incumbent, same-origin workers. To document this, for each worker starting at a new job I calculate the immigrant share of incumbent workers at that firm, and compare how immigrant and native workers differ.

The solid blue line in Figure (3) reports the average immigrant share of incumbent workers for all new jobs found. One can see that the immigrant share of new jobs for new immigrants is almost 40%, relative to 16% for natives and 17% for the economy.[5] This falls to 23% by 10 years since landing.

One could argue that this pattern reflects immigrants sorting into the same types of firms because they face similar labor market barriers or have similar levels of human capital, and then sort out over time as they assimilate. The model will allow for this. However, two things should be noted. First, these patterns are exceptionally strong: New immigrants obtain jobs on average at firms with more than a doubly over-represented share of other immigrant workers. Secondly, in the

[5]The fact that the immigrant employment share is lower than the total immigrant share reflects the fact that immigrants have a higher unemployment rate than natives.

Figure 4: Job-to-job Transition Rates and Duration Dependence



(a) Low Productivity Firms

(b) High Productivity Firms

dashed and dotted lines I report results within poach rank quartiles and find the patterns are almost identical, implying these hiring patterns cannot easily be accounted for by differences in sorting across firm types. In the estimation, I will use these patterns to discipline the parameters governing labor market networks.

2.4 Labor Market Dynamics

Finally, in this subsection I explore differences between immigrant and native workers in terms of labor market dynamics.

Figure (4) reports job-to-job transition rates for natives, established immigrants and new immigrants, where the latter are those who have been in country for 5 years or less and the former 5 years or more. I plot these separately for low and high productivity firms, defined by the first and fourth poach rank quartile. As expected, transition rates are much higher out of low productivity firms, with rates strongly decreasing with tenure duration. In the model, this duration dependence will be explained by higher productivity workers endogenously sorting away from lower productivity matches.

Three things stand out as we compare immigrant and natives. First, new immigrants have higher job-to-job transition rates on average, which one could infer as immigrants having faster job mobility up the firm ladder. However, note that immigrants have the highest mobility rates out of the

highest productivity firms, and have almost the same rates out of the lowest productivity firms. This is inconsistent with an interpretation where immigrants start employment spells "mismatched" but climb the job ladder faster. Instead, it appears that the higher job-to-job transition rates for immigrants are rather due to involuntary job reallocation. Consistent with this interpretation, I find that the poach rank of the destination firm after a job-to-job transition is consistently lower for immigrants, even conditional on where they were employed previously, and more of their transitions are down the firm ladder.

Secondly, the duration dependence patterns are noticeably flatter for immigrants. Since duration dependence is due to the selection effect of higher ability workers searching faster than lower productivity, this could be due less heterogeneity in the immigrant ability distribution. However, it can also be consistent with immigrants having less returns to search effort.

Finally, note that these patterns are converging to that of natives, with patterns for established immigrants looking much more like that of natives. This suggests that whatever drives mobility disparities dissipates as immigrants assimilate.

3 Model

In this section, I build on general equilibrium search models with two-sided heterogeneity (Postel-Vinay and Robin (2002); Lise *et al.* (2016)), endogenous vacancy creation and search effort (Bagger and Lentz (2019); Faberman *et al.* (2022)), extending to incorporate salient features of immigration, including (i) distinct worker groups that differ in labor market fundamentals, (ii) entry and assimilation of immigrant workers, and (iii) job finding through networks. The latter is important not only to do justice to survey evidence and to explain empirical hiring patterns documented in the previous section, but as I will explain theoretically in this section and demonstrate quantitatively in Section 5, networks have important implications for immigrant-native wage inequality and policy evaluation. The prevalence of job finding through the network implies each worker's labor market outcomes are related to the outcomes of their contacts, and since personal contacts are highly segregated by origin, any barriers immigrants face have external affects on their peers which further distorts immigrant sorting.

3.1 Environment

Time is continuous and all agents discount the future at rate ρ. The economy is populated by a unit mass of workers and a mass of firms N^f. Firms are heterogeneous in productivity p draw from cdf $L(p)$. Workers are heterogeneous in ability x, country of origin $c \in \mathcal{C} = \{N, 1, \ldots, C\}$, and

assimilation status $a \in \{0, 1\}$. The pair (c, a) affects both the network of contacts the worker has access to and fundamental labor market parameters to be described in the following subsections. Workers exit the labor market at rate d and a continuous mass of workers $E(x, c)$ enters the labor market to replace them, drawing their ability from their respective cdf $\Gamma(x|c)$. The distribution over country of origin N_c is exogenously set, with $N_N + \sum_{c=1}^{C} N_c = 1$. The mass of type (x, c, a) unemployed workers will be denoted by $\gamma_0(x, c, a)$, the mass of employed workers by $\gamma_1(p, x, c, a)$, and the total mass by $\gamma(x, c, a) = \gamma_0(x, c, a) + \int \gamma_1(p, x, c, a)dp$.

Workers are employed at a firm of type p or else unemployed. A fraction $\alpha(c)$ enter the labor market employed by drawing a job offer prior to entry, and the remainder enter the labor market unemployed. New immigrant workers land in the host country unassimilated ($a = 0$) and transition to assimilated over time. The process of assimilation and the distinction between native workers and new and assimilated immigrants will be articulated in the following subsection. I assume the economy is in steady state, so the mass of entrants is restricted to ensure steady-state conditions hold.[6] Let $r = \rho + d$ be the effective discount rate.

3.2 Immigrant Assimilation

New immigrants differ from natives in three main respects. First, when immigrant workers first land they may face barriers to applying their human capital accumulated prior to landing, so that their human capital in the host country is $h(x, c) \equiv \tau_h(x, c)x$, $\tau_h(x, c) \leq 1$. Here, I view x as the workers *innate* ability upon entering the labor market, and $h(x, c)$ as *effective* ability. Intuitively, this allows for the fact that not all of an immigrants human capital is immediately transferable across countries. Imperfect knowledge of host country institutions, language and culture, or formal barriers like occupational certifications may render immigrants temporarily less productive. The severity of these barriers is allowed to vary by the immigrants ability x to allow for the possibility that these types of barriers may be more or less severe for certain types of workers.

Secondly, in addition to barriers that affect an immigrant workers productivity within any given job, they may also face barriers that affect how efficiently they sort across jobs. Imperfect knowledge of institutions may impede immigrants ability to search for employment, lack of language proficiency may affect the quality of their applications and interviews, and lacking formal cre-

[6] A more flexible immigrant entry scheme would be interesting but would require out of steady-state dynamics, which are notoriously difficult to keep tractable in search models with two-sided heterogeneity. Elsby and Gottfries (2022) make some headway, allowing for out of steady-state dynamics in a model with homogeneous workers. Lise and Robin (2017) allow for aggregate dynamics in a similar environment to here, but require the restriction that workers have no bargaining power. There they focus on aggregate employment dynamics induced by fluctuations in a scalar aggregate productivity shock. Imposing this assumption in a simpler version of the current model generated unsatisfying wage dynamics in response to immigration shocks.

dentials may disqualify them from certain jobs. Moreover, discrimination may reduce the set of firms willing to hire new immigrants. These types of barriers may hinder immigrants from efficiently sorting into jobs relative to native workers with the same effective human capital. I model these "allocational" barriers by allowing immigrants and natives to differ in terms of labor market fundamentals, primarily those parameters governing the immigrants search technology.

Finally, and as documented in section 2.3, new immigrants will have a different network of personal contacts than native workers that affects their access to job opportunities. In Section 3.4 I show theoretically that between-group differences in labor market contacts provides a novel micro foundation for barriers that distort the allocation of immigrant labor relative to native workers.

To capture the fact that immigrants converge to natives in labor market outcomes with time in the host country, I employ a simple modeling device where new immigrant workers endogenously apply effort η at convex cost $c_\eta(\eta)$ to "assimilate". Formally, at rate η the worker receives a "native shock" that results in the removal of human capital and allocational barriers and moves the worker into the native network.[7] Assimilated immigrants are therefore equivalent to a same-ability native worker in all respects other than endogenously having a different employment distribution dynamically inherited from their time as a new immigrant.

3.3 Value functions and wages

Since assimilated immigrants share the same parameter space and value functions as natives, let the workers "group" be $g = N$ for native and assimilated workers, and $g = c$ for unassimilated workers from country c. Let $W_0(x, g)$ and $W_1(p, w, x, g)$ denote the value functions for workers of type (x, g) who are unemployed or employed at a type p firm and making wage w, respectively, and let $S(q, x, g)$ denote the surplus from the match.

I assume wages are set following the bargaining protocol of Cahuc *et al.* (2006) where workers have bargaining share $\beta(g)$. A type (x, g) worker at firm p who was hired out of unemployment is given a wage $\phi^u(p, x, g)$ such that

$$W_1(p, \phi^u(p, x, g), x, g) - W_0(x, g) = \beta(g)S(p, x, o)$$

Following Lise *et al.* (2016), the wages of a worker poached from another firm $p \geq q$ (denoted by $\phi^p(p, q, x, g)$) or who received an outside offer from $q < p$ and stayed with p (denoted by

[7] One could alternatively assume the worker maintains their original immigrant network, but this would fail to capture the fact that immigrants also socially assimilate over time, reporting less jobs found through same-ethnicity contacts as they spend time in Canada. The current set-up also has a computational benefit in that assimilated immigrants and native workers share the same value functions.

$\phi^s(p,q,x,g)$) are determined implicitly by,

$$W_1(p,\phi^p(p,q,x,g),x,g) - W_0(x,g) = \beta(g)S(p,x,o) + (1-\beta(g))S(q,x,o)$$
$$W_1(p,\phi^s(p,q,x,g),x,g) - W_0(x,g) = S(q,x,o).$$

For simplicity, I assume new immigrants make their optimal assimilation decision prior to landing in order to maximize lifetime value,

$$\eta(x,c) = \arg\max_{\eta} W_0(x,N) - W_0(x,c) + \alpha(c)\int [S(p,x,N) - S(p,x,c)]d\Lambda(p,g) - c_\eta(\eta),$$

where $\Lambda(p,g)$ is the distribution of job offers. Workers also choose their search effort s subject to a convex cost function $c(s)$ and their expected payoffs which will be conditional on their type and labor market position. Let $i \in \{0,1\}$ denote whether the worker is unemployed or employed, respectively. I assume a linear search intensity function $\mu_i(g) + \kappa_i(g)s$, where $\kappa_i(g)$ is the return to search effort and $\mu_i(g)$ is passive (or free) search.[8] The value function for an unemployed worker is then,

$$rW_0(x,g) = \max_{s\geq 0}\Big\{b(h(x,g),g) - c(s) + \eta(x,g)[W_0(x,N) - W_0(x,g)] + [\mu_0(g) + \kappa_0(g)s]\overline{\lambda}(g)\beta(g)\int_{\underline{p}}^{\overline{p}} S(q,x,g)d\Lambda(q,g)\Big\} \tag{3}$$

where $h(x,g) = \tau_H(x)x$ for $g \in \{1,\ldots,C\}$ is new immigrants effective human capital. Note that $h(x,N) = x$ and $\eta(x,N) = 0$. Unemployed workers with effective human capital h receive benefits $b(h,g)$ and obtain job offers at rate $\overline{\lambda}(g)$ per unit of search intensity. Once matched with a

[8]The cost function for search effort is assumed to be the same whether unemployed or employed. One might expect search to be more costly when simultaneously holding a job, since one has less free time to devote to search. This intuition is confirmed in Faberman *et al.* (2022), where their survey data allows them to separately identify the returns to search parameters (κ_i) from the cost shifter in $c_i(s)$. Here, my administrative data does not permit separate identification of these parameters. This implies that differences between κ_0 and κ_1 reflect not only differences in returns to search but differences in the cost of searching as well.

firm of type p, the worker and firm generate flow production $f(p,h)$ and have joint match value

$$\begin{aligned} rP(p,x,g) = \max_{s\geq 0} \Big\{ & f(p,h(x,g)) - c(s) + \eta(x,g)[P(p,x,N) - P(p,x,g)] \\ & + (\delta_r(g)\overline{\lambda}(g) + \delta(x,g))[W_0(x,g) - P(p,x,g)] \\ & + [\mu_1(g) + \kappa_1(g)s]\overline{\lambda}(g)\beta(g) \int_p^{\bar{p}} [P(q,x,g) - P(p,x,g)] d\Lambda(q,g) \\ & + \delta_r(g)\overline{\lambda}(g)\beta(g) \int [P(q,x,g) - W_0(x,g)] d\Lambda(q,g)^{n(x)} \Big\}. \end{aligned} \tag{4}$$

Employed workers receive an exogenous separation shock at rate $\delta(x,g)$ and an exogenous involuntary job reallocation shock at rate $\delta_r(g)$. In the latter case the worker draws $n(x)$ job offers and accepts the best one. As in Bagger and Lentz (2019) I assume for tractability that employed workers choose on-the-job search effort to maximize joint match value.

Finally, firms face a continuous vacancy posting cost and therefore as in Lise and Robin (2017) the value of an unfilled vacancy is zero. Therefore, match surplus is $S(p,x,g) \equiv P(p,x,g) - W_0(x,g)$ and one gets the following surplus equation

$$\begin{aligned} (r + \eta(x,g) + \delta_r(g)\overline{\lambda}(g) + \delta(x,g))S(p,x,g) = & f(p,h(x,g)) - b(h(x,g),g) \\ & + \max_{s\geq 0} \Big\{ [\mu_0(g) + \kappa_0(g)s]\overline{\lambda}(g)\beta(g) \int S(q,x,g) d\Lambda(q,g) - c(s) \Big\} \\ & + \max_{s\geq 0} \Big\{ [\mu_1(g) + \kappa_1(g)s]\overline{\lambda}(g)\beta(g) \int_p^{\bar{p}} [S(q,x,g) - S(p,x,g)] d\Lambda(q,g) - c(s) \Big\} \\ & + \delta_r(g)\overline{\lambda}(g)\beta(g) \int S(q,x,g) d\Lambda(q,g)^{n(x)} + \eta(x,g)S(p,x,N) \end{aligned} \tag{5}$$

In this model, between-group differences in sorting will arise for three main reasons. First, immigrant workers may have lower human capital, either because their initial distribution is lower or because they face barriers to transferability ($\tau_H(x) < 1$). When f is super-modular workers with higher ability will obtain more gains from sorting into higher productivity firms and will therefore optimally choose to apply higher effort s to sort away from "bad" (low productivity) matches. This implies that human capital barriers limit the returns to obtaining higher productivity matches, reducing the incentive for immigrants to search intensively and therefore leading them to optimally settle in lower productivity matches.

Secondly, immigrants may have worse search technology $\{\mu_0, \mu_1, \kappa_0, \kappa_1\}$, job stability $\{\delta, \delta_r\}$, or bargaining position $\{b, \beta\}$ such that their incentives to search and returns from search are lower relative to a native with the same effective human capital h, resulting in immigrants being less optimally sorted compared to native workers.

Finally, note that workers discover new job opportunities at a total rate of $\overline{\lambda}(g)$ per unit of search intensity with distribution over firm types given by the cdf $\Lambda(p, g)$. The fact that the rate and distribution of job opportunities differs by group is a product of labor market networks: Immigrants have different personal contacts than natives, and the efficacy of these contacts to provide good job information will depend on their own labor market position and labor market barriers. I now turn to describe labor market networks in more detail.

3.4 Networks and Matching

All workers are connected to a network that permits the transmission of job information. Consistent with the evidence presented in 2.3, I assume that networks are exclusive between-g. For simplicity I also assume networks exhibit no within-origin homophily patterns, implying that information is passed randomly within the network as opposed to being directed to certain types of workers.[9] I follow the search literature in assuming perfect information about the value of a match, so in contrast to Dustmann *et al.* (2016) and Moon (2023), networks only function to share job information to facilitate a meeting between workers and potential employers. Moon (2023) finds this is quantitatively the most important function of labor market networks.

Jobs can be found through one of three channels. First, the "formal" channel includes meetings generated directly between a worker and a firm. This would include jobs found in response to newspaper or online ads, or direct application to the employer. This channel is modeled by the stochastic generation of meetings between workers and firms. Specifically, a mass of meetings $M(N^s, N^v)$ is continuously produced and distributed to workers at Poisson rate $M(N^s, N^v)/N^s$ per unit of search intensity, where $N^s \equiv \sum_g N^s(g)$ is the total search mass in the economy and

$$N^s(g) \equiv \int [\tau_0(g) + \kappa_0(g) s_0(x, g)] \gamma_0(x, g) + \left\{ \int [\tau_1(g) + \kappa_1(g) s_1(q, x, g) + n(x)\delta_r(g)] \gamma_1(q, x, g) dq \right\} dx$$

is the total search mass for workers from origin g, and $s_0(x, g)$ and $s_1(q, x, g)$ are optimal search effort conditional on the workers type and labor market status.

Secondly, a job may be found via a personal contact employed at a firm with an open vacancy, which will be referred to as the "business referrals" channel. Finally, a personal contact who is external to the firm may nevertheless hear about one of their vacancies and pass that information onward, which will be referred to as the "personal referral" channel. I now explain how such job referrals networks function in the model.

[9] This is a natural benchmark and is the most one can do without more detailed data on network connections.

3.4.1 Vacancy Posting and Business Referrals

Let N^v be the total mass of vacancies in the labor market. Each firm of type p chooses how many vacancies to post v subject to a per-period vacancy posting cost $c_V(v)$,

$$v(p) = \arg\max_{v} v\Pi_0(p) - c_V(v) \tag{6}$$

where

$$\Pi_0(p) = \frac{M(N^s, N^v)}{N^v}\left(\sum_g \frac{N^s(g)}{N^s}\overline{\Pi}(p,g) + \max_{\phi}\left\{\phi\sum_g \tilde{\gamma}(g|p)\overline{\Pi}(p,g) - c_B(\phi)\right\}\right) \tag{7}$$

is the expected value of a vacancy. Here $\overline{\Pi}(p,g)$ is the expected value to the firm of meeting a worker from group g, taking into consideration the probability of it ending in a match, and $\tilde{\gamma}(g|p)$ is the group distribution of workers employed at p. Vacancies can be filled by simply waiting to meet a worker formally (at rate $M(N^s, N^v)/N^v$), but firms can also apply internal recruiting effort $\phi(p)$, in which case their existing employees also send out the job information to their network. Meetings generated this way are referred to as internal/business referrals. Note that here the firm incurs a cost to use internal referrals $c_B(\phi(p))$. I think of this as a combination of additional effort/resources used for informal recruiting as well as referral bonuses paid to the referrer. However, for simplicity I do not explicitly model the transfer of such bonuses in the workers utility.[10] Here I let the rate and cost of business referrals be proportional to the formal meeting rate, so that the total meeting rate for business referrals is $\phi M(N^s, N^v)/N^v$. As shown later on, this formulation permits a closed-form expression for labor market tightness, which is critical computationally.

3.4.2 Personal Referrals

A group g worker holding job information p who is already employed at a higher rank firm q is assumed to altruistically care about their personal contacts and is therefore willing to incur some cost $c_P(\psi)$ to pass this job information to one of their contacts with probability ψ. Let $\overline{W}(p,o)$ be the expected value of a meeting with p to a random contact in the worker's network in the informal

[10] Otherwise the firms vacancy posting problem enters into the match surplus equation, which would be a needless complication as long as most workers do not make their employment decisions based on the potential to receive referral bonuses.

stage. The optimal value of ψ is then[11]

$$\psi(p,g) = \arg\max_{\psi} \psi \overline{W}(p,g) - c_P(\psi) \tag{8}$$

where c_P is an increasing convex function with $c_P(0) = 0$. Meetings generated in this way are referred to as external or "personal" referrals.

3.4.3 Total Job Finding Rate

A worker can therefore discover a job opportunity in one of three ways: through meetings generated via the meeting function M (formal channel), through a workers contact whose employer is internally recruiting (business referral channel) or through a workers contact who does not work at the firm but is aware of the job opening and is willing to share that information (personal referral channel). Define,

$$R(p,g) \equiv \frac{1}{N^s(g)} \int \int_{p}^{\bar{p}} [\mu_1(g) + \kappa_1(g) s_1(q,x,g)] \gamma_1(q,x,g) dq dx$$

as the probability that a worker in g who finds a type p job is already employed in a higher rank firm and is therefore willing to pass the opportunity. In the appendix I show that the total rate of finding a type p job per unit of search effort is,

$$\begin{aligned} \bar{\lambda}(g)\lambda(p,g) &= \bar{\lambda}^F(p) + \bar{\lambda}^B(p,g) + \bar{\lambda}^P(p,g) \\ &= \bar{\lambda}^F(p) \underbrace{\left(1 + \frac{\phi(p) N^s \tilde{\gamma}(g|p)}{N^s(g)}\right)}_{\text{Business referral multiplier}} \underbrace{\left(\frac{1}{1 - \psi(p,g) R(p,g)}\right)}_{\text{Personal referral multiplier}}, \end{aligned} \tag{9}$$

where $\bar{\lambda}^B(p,g)$, $\bar{\lambda}^P(p,g)$, and $\lambda^F(p) \equiv \frac{M(N^s,N^v)}{N^s} \frac{N^v(p)}{N^v}$ are the business, personal, and formal rate of job finding per search unit.

Equation (9) states that that the total job finding rate is equal to the formal job finding rate times two group-specific multiplier terms that arise due to the presence of labor market networks.[12] That the decision to use business (personal) referrals is endogenous to the firm (worker) has some intuitive properties that generates empirically consistent predictions. First, higher productivity

[11] Note that this assumes workers are fully altruistic in the sense that the referring worker places equal weight on their utility and the utility of the receiving worker. This is without loss of generality, since any weight parameter will be isomorphic to the cost parameters in c_P.

[12] Note that I implicitly assume the worker makes one search effort decision that effects the returns to both formal and referral channels. One could alternative allow the worker to make unilateral search decisions through each channel, as in Moon (2023).

firms have a higher incentive to use business referrals since the expected surplus is larger for these jobs ($\phi'(p) > 0$) which is consistent with empirical evidence that business referrals are associated with a wage premia (Arbex *et al.* (2019), Moon (2023), Lang and Yang (2024)).

Second, the distribution of job opportunities coming through personal referrals will also be fundamentally different than the formal channel due to three competing effects: (1) They must first be rejected by workers who are already employed in a better job, which lowers the distribution ($\partial R(p,g)/\partial p < 0$), (2) workers are more likely to pass good (high-surplus) job information, conditional on it being inferior to their own position, since the expected surplus of generating a meeting is higher ($\partial \psi(p,g)/\partial p > 0$), and (3) search intensity falls as one climbs the job ladder, implying workers employed at high-rank firms (who are willing to pass high rank job information) are obtaining new job information at lower rates.[13] Whether or not the average job found through the personal channel is of a higher or lower rank than that of the formal channel is therefore theoretically ambiguous, however I find that the first and third effect dominate and that personal referrals are associated with lower paying jobs, consistent with empirical evidence that personal referrals are associated with a wage penalty (Moon (2023), Lang and Yang (2024)).

But most importantly, this equilibrium job finding function in equation (9) is the key for understanding how networks contribute to between-group wage inequality. If $\phi(p) = \psi(p,g) = 0$ then there are no labor market networks and all workers face the same job arrival function. However, when $\phi(p) > 0$ and/or $\psi(p,g) > 0$, the rate and the distribution of job opportunities a worker has access to now depends on both the search behavior and the employment distribution of their personal contacts. If immigrants face labor market barriers, they will, in equilibrium, be employed at lower rank firms than native workers. Since higher rank firms will use business referrals more intensively, this gives native workers preferential access to high productivity job information, as they are more likely to have personal contacts in those firms. Similarly, since $R(p,g)$ is increasing in the employment mass of group g workers with firm type $q > p$, native workers will typically be in a better labor market position to provide job information to their personal contacts.

Note that workers have a higher incentive to generate personal referrals when their network is in a worse labor market position since the expected surplus from generating an informal meeting will be higher. This means that, consistent with empirical evidence, immigrants may have a higher incentive to use personal referrals (Carlsson *et al.* (2018), Alaverdyan and Zaharieva (2022)). Whether immigrants use personal referrals more or less than natives is therefore theoretically ambiguous. Regardless, the *distribution* of jobs flowing through immigrant personal referrals will be lower

[13] The essence of the first effect is present in Galeotti and Merlino (2014). In Galeotti and Merlino (2014), the endogenous network intensity functions from the side of the worker searching for information, not the worker sending it. The implications are identical. The second and third effect arises from heterogeneous firm types and endogenous seach intensity, both of which are absent from their model.

than natives, and therefore through both personal and business referrals the network structure of the labor market has the potential to amplify inequality between groups.

4 Estimation

4.1 Parametrization and Identification

In this section I specify the exact functional forms used in the estimation of the model and discuss identification of parameters. The parameter space is exceptionally large in this model, partly due to the inclusion of networks and other features important for the context of immigration, and partly due to different parameter spaces for each worker group. I therefore set parameters exogenously wherever possible, either by making normalizations, inferring from the empirical section, or borrowing parameters from the literature, freely estimating only the parameters that are key for understanding immigrant assimilation.

Functional forms. I assume cost functions for search effort, vacancy posting, business referrals, and immigrant assimilation follow the familiar functional form $C_J(j) = c_{J0} j^{1+1/c_{J1}}/(1+1/c_{J1})$, $J \in \{S, V, B, A\}$. The cost function for personal referrals is assumed to take the form $C_P(\psi) = \max\{-ln(\frac{1-\psi}{1-c_{P0}})^{c_{P1}}, 0\}$. This ensures the referral probability is bounded in the interval $[c_{P0}, 1]$, where $c_{P0} \geq 0$ is interpreted as the extent of effortless information sharing. Worker and firm productivity types are assumed to be distributed according to a Rayleigh distribution, akin to a one-parameter log-normal, with scale parameters $\alpha_x(g)$ and α_p. A match between a firm of productivity p and a worker with effective human capital h has flow output $f(p,h) = (f_0 h^{f_1} + (1-f_0)p^{f_1})^{1/f_1}$, where f_0 is the weight on workers human capital in production and f_1 governs complementarity. I assume workers flow value of unemployment will be given by $b(h,g) = f(b_0(g), h)$ and follow Faberman *et al.* (2022) in letting $\delta(h,g) = \delta_0(g) - \delta_1(g)ln(h)$ to accommodate the fact that separation rates vary by worker type. Finally, I discipline the human capital barriers function with a logistic form $\tau_H(h) = 1/(1+\tau_{H0}e^{-\tau_{H1}h}) \in (0,1)$ where τ_{H0} sets the level for the lowest productivity workers and τ_{H1} the extent to which barriers are different for high productivity workers.

Search and transition technology. I set $\delta_0(g) = \delta_0$ and $\delta_1(g) = \delta_1$ since, as documented the empirical section, there does not appear to be meaningful differences between immigrants and natives in terms of match separation shocks conditional on firm types.[14] I set δ_0 and δ_1 ex ante to approximate observed separation rates. The evidence on J-J transitions out of high-rank firms and down the firm ladder suggest that immigrants experience higher rates of job instability, and the difference between immigrants and natives in terms of destination ranks conditional on source rank

[14] Immigrants may still have higher separation rates on average if they are lower productivity.

suggest that this process is well-approximated by a scalar multiplicative difference in reallocation rates. I identify the reallocation rates of natives $\delta^r(N)$ and immigrants $\delta^r(I)$ using the native rate of J-J transitions out of the highest firm poach decile and the repsective difference in rates between natives and new immigrants.

The search technology for unemployed native workers $\mu_0(N)$ and $\kappa_0(N)$ are identified based on average transition rates out of unemployment and accompanying duration dependence patterns. I will use monthly U-J transition rates conditional on the worker having already been unemployed for 0 and 12 months. The search cost shifter C_{S0}, which governs overall search efficiency, is then identified using native J-J transition rates out of the lowest rank firms. Since the returns to search effort for both unemployed and employed workers is not identified separately from C_{S0} without explicit data on search effort, I follow Bagger and Lentz (2019) in normalizing $\kappa_1(N) = 1$. I then set $\mu_1(N) = 0.6\mu_0(N)$ and $C_{S1} = 3.6$ following estimates in Faberman *et al.* (2022).

In the empirical section we saw that the difference in J-J transition rates between immigrants and natives is highest at the highest rank firms, and about the same at the lowest rank firms. Since the data also imply immigrants have a higher fraction of involuntary job transitions along the firm rank distribution, this implies immigrants have a lower rate of voluntary J-J transitions. We also saw that the J-J duration dependence is flatter for immigrants, which is consistent with lower returns to on-the-job search effort, and that they have a lower rate of U-J transitions. While we could estimate all immigrant search parameters freely, the aforementioned facts suggests the differences in search technology between immigrants and natives is consistent with a single multiplicative scalar $\tau_S leq 1$ reducing their overall search efficiency. I therefore set, $\mu_i(I) = \tau_S \mu_i(N)$, $\kappa_i(I) = \tau_S \kappa_i(N)$ for $i \in \{0, 1\}$ and estimate τ_S using the difference between the native and new immigrants job-to-job transition rate out of the lowest rank firms.[15]

Networks. Business referrals will be associated more with higher rank firms, and personal referrals will be used more for lower rank firms. The parameters governing personal and business referrals will therefore be identified using the strength of ethnic hiring and segregation patterns along the firm rank distribution. Specifically, I use the correlation between immigrant share of new hires and existing employees for high and low rank firms, and a segregation index.

Assimilation. The key parameters governing immigrant assimilation, in addition to networks and the differences in search and transition parameters discussed above, are the parameters governing human capital barriers and assimilation costs. Human capital barriers will be disciplined to match wage assimilation not explained by differences in search technology and networks.

Productivity. The distribution of immigrant worker productivity relative to natives is determined

[15] Can throw in other immigrant transition moments as well.

by differences in wages that remain after all immigrant workers have assimilated. Although we never fully observe this figure, our assimilation estimates imply that by 20 years immigrant wages are the same as native workers. I therefore make the simplifying assumption that the distribution of *potential* human capital (i.e., the distribution they converge to as they dispense with barriers to applying their human capital) is the same.[16] I therefore set $\alpha_x = \alpha_{xI} = \alpha_{xN}$ and estimate α_x using the total variance of log wages.

The flow value of unemployment $b_0(g)$ and bargaining power $\beta(g)$ affect wage dynamics over a continuous employment spell. A lower value of $b_0(g)$ will cause workers to begin employment spells farther below the average wage followed by larger wage increases. A lower value of $\beta(g)$ will also generate lower initial wages, but will allow the worker to capture smaller wage gains condition on J-J movements. The data suggest that immigrant and native workers do not differ substantively along these dimensions: Both groups of workers begin employment spells roughly 20 log points from their respective means and have similar wage growth over the employment cycle. Immigrant workers have slightly larger wage gains conditional on J-J mobility, a feature that will naturally be produced by the fact that $\tau_S < 1$ lowers their initial bargaining position. I therefore normalize $b_0(N) = b_0(I) = p_{min}$ and $\beta(N) = \beta(I) = 0.5$.

This leaves us with 17 parameters to estimate,

$$\theta = [\mu_0(N), \kappa_0(N), \delta^r(N), \delta^r(I), \tau_S, \tau_{H0}, \tau_{H1}, C_{S0}, C_{V1}, C_{P0}, C_{P1}, C_{B0}, C_{B1}, C_{A1}, f_1, \alpha_x, \alpha_p]$$

4.2 Computation

To estimate the model, I discretize worker and firm types into $X = P = 25$ nodes and for each coefficient vector θ solve the fixed point problem by starting with initial guess $S^0(p, x, g) = f(p, x, g) - b(x, g)$ and $\bar{\lambda}^0(p, g) = \ell(p)$ and iterating over (5) and (9). Using this solution, I simulate employment histories for a 1% sample of workers and calculate the vector of simulated moments $\omega_S(\theta)$ identically as in the data $\omega$and solve

$$\hat{\theta} = \arg\min_{\theta} [\omega_S(\theta) - \omega]' W [\omega_S(\theta) - \omega] \tag{10}$$

Since the model is exactly identified, I follow a similar approach to Taber and Vejlin (2020) and weight moments by the inverse of their absolute value. In this current working draft, I set parameters exogenously to qualitatively capture the salient patterns observed in the data. In particular, I set $\delta_r(I) = 0.01 > \delta_r(N) = 0.005$, $\tau_{H0} = 1.0$, $\tau_{H1} = 0.15$, and $\tau_S = 0.5$. The human capital

[16] Another way of putting this is that in a counterfactual world where the stock of immigrants were born into the host country, under the host countries institutions, language, etc. they would have the same distribution of ability.

barrier parameters imply $\tau_H(\underline{x}) = 0.35$ for the lowest productivity worker, rising to $\tau_H(\overline{x}) = 0.75$ for the highest productivity worker.

4.3 Model fit

Forthcoming.

5 Counterfactual exercises

In this section I briefly highlight the productivity implications of immigrant barriers.

5.1 Counterfactual #1: Complete immigrant assimilation

I begin by allowing immigrant workers to completely assimilate such that they are identical to an equally productive native worker. I view this as a benchmark for the potential gains from improved immigrant integration. Under this simple specification I find room for significant productivity gains: If immigrants could land in country fully assimilated, they would on net generate 40% more output relative to baseline. This reflects three factors: (1) Immigrants will be more likely to be employed, (2) they will be sorted into higher productivity matches, and (3) they will be more productive in those matches. This large increase in immigrant productivity combined with the fact that immigrants make up one-fifth of the labor force results in large total output gains of 12.5%.

5.2 Counterfactual #2: Removing job search barriers

The differences in search parameters between native and immigrant workers relate to any additional barriers immigrants face in finding employment. Plausible labor market barriers unique to new immigrants could be lack of language proficiency, lack of soft skills such as resume writing and interview preparation, less information on how to effectively search for employment, employer uncertainty over worker credentials that gives preference to native applicants, or discrimination. These are the focus of Canada's IRCC Settlement Program, which helps immigrants develop language proficiency, job search and other employment-related skills, and general information about Canadian culture and labor markets.

Here I explore the implications of setting $\tau_S = 1$ and $\delta_r(I) = \delta_r(I)$, while leaving human capital and networks differences as in the baseline. I again find substantial output gains. The average immigrant contribution to productivity increases by 12.2%, primarily by increased sorting into higher productivity firms. This reallocation alone generates total output gains of 5.8%, almost half that from full assimilation.

6 Conclusion

This paper aims to better understand immigrant wage assimilation, including its underlying sources and implications for aggregate productivity. I carefully document differences between native and immigrant workers in terms of firm types, labor market dynamics, and ethnic hiring patterns, and argue that immigrants face both human capital barriers and allocational barriers, the latter stemming from a combination of search frictions and segmented labor market networks.

I then develop a general equilibrium model of the labor market that can capture these differences and use it to quantify the productivity losses due to immigrant labor market barriers and to understand what drives immigrant wage assimilation.

Immigration rates are reaching all-time highs in developed countries and are predicted to continue this way into the future. A fundamental policy challenge for these countries is how to maximize the economic contribution of immigrant workers. This is a challenge because the data suggest immigrants face unique barriers that hinder their integration into the labor market, rendering them temporarily less productive than they otherwise could be and more poorly allocated across firms. It is the hope that this work can not only quantify how important these barriers are but offer some helpful guidance into what types of integration policies will be effective.

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