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

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Abstract

I study how barriers to labor market integration shape immigrant outcomes and the aggregate economy. Using matched employer–employee data from Canada, I document new and detailed differences between immigrants and natives in terms of earnings, labor market dynamics, and sorting patterns across firms. Guided by these facts, I develop and estimate a search model with two-sided heterogeneity, sorting, referral networks, and dynamic between-group inequality. A quarter of the gap in earnings and half of the gap in firm sorting is driven by allocational barriers—a combination of lower effective job search, higher job instability, and segmented referral networks—rather than differences in worker skills. Eliminating these barriers would raise immigrant output by 8.4% and total output by 1.1% by increasing immigrant employment and allowing them to reallocate into higher productivity firms. Feasible integration programs that combine human capital investments with search assistance deliver similar output gains. These gains are achieved without harming native workers due to firms' endogenous job-creation response. The counterfactuals highlight that integration programs should target unemployed low-skill immigrants.

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1 Introduction

This paper studies how barriers to labor market integration shape immigrant outcomes and the aggregate economy, distinguishing between an immigrant's *ability* and their *allocation* across firms. Since the seminal work of Chiswick (1978) and Borjas (1985), one of the most studied empirical patterns in the economics of immigration has been 'assimilation'—the observation that new immigrants earn substantially less than comparable natives but gradually close this gap with time in the host labor market. Economists typically attribute this pattern to lower initial skills followed by investment, which could account for both the initial earnings gap and subsequent convergence (e.g., Borjas (2015); Albert *et al.* (2021); Adda *et al.* (2022)). However, there is also evidence that immigrants face barriers beyond differences in skills: discrimination, slow recognition of foreign credentials, and weaker professional networks can limit an immigrant's job opportunities relative to an equally skilled native (e.g., Oreopoulos (2011); Brücker *et al.* (2021)). It is therefore unclear to what extent the observed inequality reflects differences in worker ability versus barriers that impede the allocation of immigrant labor.

Understanding the microeconomic sources of immigrant-native inequality is important not only for concerns over fairness, but also because it may signal the misallocation of a substantial share of labor. Moreover, whether immigrants earn less because they lack skills or because they cannot access suitable jobs has direct implications for immigration policy: should integration programs prioritize skill investments or addressing impediments to job finding? Quantifying the aggregate gains from removing these barriers is equally important for setting policy priorities: what is the appropriate scale of such policy efforts? Yet distinguishing between these sources is empirically challenging. Worker ability is unobserved, and even recent evidence showing that immigrants sort into lower-productivity firms (Dostie *et al.* (2023); Arellano-Bover and San (2023); Lehrer and Rawling (2025)) cannot by itself disentangle whether this reflects assortative matching or allocative distortions.

In this paper, I combine a rich empirical analysis of immigrants in the labor market with a structural model to disentangle the underlying sources of immigrant-native inequality and to quantify the aggregate implications of immigrant labor market barriers. I start by using matched employer–employee tax-file data from Canada to document detailed and novel differences between immigrants and natives not only in earnings, but also in labor market dynamics and sorting patterns across firms. I find evidence that immigrants have higher job instability, barriers to finding employment from unemployment, and exhibit strong co-national sorting patterns consistent with ethnically segmented referral networks. I then develop and estimate a labor market search model featuring two-sided heterogeneity, sorting, referral networks, and immigrant assimilation. I find that differences in human capital alone are insufficient to explain the observed empirical

patterns—immigrants also face allocational barriers, receiving fewer job offers per unit of search effort, losing jobs more often, and having less access to higher productivity job information because of segmented referral networks. Quantitatively, these barriers explain about one-quarter of the earnings gap by limiting immigrant access to high-productivity jobs. Removing allocational barriers would raise immigrant output by 8.4%, through both higher employment and reallocation toward more productive firms. Finally, I evaluate feasible policy interventions, finding that language training programs (LTPs) and active labor market policies (ALMPs) would significantly raise immigrant wages and output through a combination of human capital investment and improving job search effectiveness. The model also clarifies the mechanisms through which reducing allocational barriers leads to output gains, the competition this places on native workers, and overall provides a unified theory for why immigrants earn lower wages and sort into lower-productivity firms.

To analyze how immigrants differ from natives in the labor market and the dynamics of how these gaps evolve over time, I combine administrative data on all workers and firms in Canada from 2001–2019 with detailed immigrant landing records. This dataset allows me to identify immigrant workers in the tax records and provides a rich set of immigrant observables such as their country of origin, date of arrival, and channel of entry. Using an assimilation regression that exploits within-worker changes in outcomes, I find that immigrants have monthly earnings 61 log points less than comparable natives upon arrival, with this gap narrowing to 15 log points after 20 years. New immigrants also differ substantially in the types of firms they work in, initially sorting into lower paying, lower productivity firms.

The unclear sources of this immigrant-native inequality in earnings and firm sorting motivates exploring the other ways in which immigrants and natives differ in the labor market. I document three new facts about immigrant labor market dynamics and sorting patterns that do not seem to be easily explained by differences in worker skill. First, immigrants have higher job instability: they transition out of their jobs at 50% higher rates than comparable natives in similar jobs and are more likely to move down the firm ladder and into unemployment. Second, immigrants appear to face barriers to job finding: conditional on entering unemployment, native workers find employment 25% faster even relative to immigrants who were previously employed in similar firms with similar earnings. Third, immigrants have a different network of personal contacts for job finding: almost half of their jobs are found through their contacts and about 90% of these contacts are of the same ethnicity. Consistent with such ethnically segmented referral networks, I document that immigrants disproportionately join firms with a higher share of co-national incumbent employees. These gaps speak directly to how immigrants are sorting across firms and strongly suggest there are other features of the labor market beyond differences in skills that affect the allocation of immigrant workers.

While other work has documented immigrant-native differences in labor market dynamics (e.g., Albert *et al.* (2021)), doing so using rich administrative data where one can observe how these relationships vary across time, the firm distribution, and immigrant groups is novel, and will be instrumental in the estimation of the structural model. Similarly, other work has emphasized that immigrants sort into firms with a higher share of co-ethnic incumbents (e.g., Gyetvay and Keita (2024)), but I am the first to formally link these patterns to referral networks and assess their implications for wage inequality, sorting, and aggregate productivity.

I then develop a structural model of the labor market to understand what these empirical facts imply for immigrant-native inequality and aggregate productivity. The model features heterogeneity in worker and firm productivity and positive assortative matching, building on the framework of Bagger and Lentz (2019). The main theoretical innovations are to allow for dynamic immigrant assimilation and to explicitly embed job finding through referrals into a rich search model with heterogeneous workers and firms. When immigrants first arrive, they are allowed to differ from natives in a number of dimensions—including effective skills, search and transition technology, and their network of personal contacts—which micro-founds the sources of immigrant-native inequality in earnings and firm sorting. For example, immigrants may have imperfect transferability of skills, implying they are less productive than natives when starting out in the host labor market. As lower-productivity workers, immigrants will earn lower wages and sort into lower productivity firms in equilibrium. However, immigrants may also face other challenges that directly impact how they find employment and move up the firm ladder—such as having lower job stability, lower search efficiency, or a lower-quality network of personal contacts. I show both theoretically and quantitatively that segmented referral networks create unequal access to job information that significantly affects the allocation of immigrants across the firm distribution. Consistent with the data, immigrants then become more like native workers over time by endogenously applying effort to gain skills and overcome the barriers they face at landing. Workers also choose how intensively to search for work, and firms choose how intensively to recruit new workers, both formally and through their incumbent workers.

I estimate the model by indirect inference, exploiting immigrant-native differences in wages and sorting patterns to identify the key parameters governing immigrant-native inequality. For example, differences in worker skills alone could in principle explain the differences in earnings, but fails to capture why immigrants are more likely to move from higher to lower productivity firms or why they exhibit co-national sorting patterns. Gaps in these other outcomes provide the variation needed to identify the parameters governing search efficiency, job instability, and referral networks. The estimated model captures a comprehensive set of moments that characterize the dynamic labor market experience of immigrants, and suggests immigrants face both imperfect transferability of skills and allocative barriers. Importantly, the model also replicates the observed

differences between immigrants and natives in terms of firm productivity, despite these moments being untargeted in the estimation. The model's ability to naturally replicate these sorting gaps indicates that its microfoundations capture how integration barriers shape immigrant allocation.

I structurally decompose immigrant assimilation and find one-quarter of differences in earnings and one-half of differences in firm sorting are caused by a combination of search barriers, job instability, and segmented referral networks. Because social assimilation is slow, referral networks play a particularly important role in driving immigrant-native gaps in allocation across firms in the long run. These allocational barriers have substantial implications for the aggregate economy, lowering immigrant output by 8.4% and total output by 1.1%. The output losses arise from a combination of immigrants allocating into lower productivity jobs (intensive margin), decreasing immigrant employment (extensive margin), and by decreasing immigrant investment in host country specific skills. Interestingly, the output losses largely stem from the decreased employment of *low-skill* immigrants. High-skill immigrants have the largest incentives to assimilate and therefore quickly overcome the barriers they face through higher effort. In equilibrium, low-skill immigrants struggle the most, and therefore it is these workers who have the largest response to policy efforts. The relevant insight that emerges from this analysis is that integration programs that target lower-skill unemployed immigrants will have the largest impact on output.

While improving immigrant outcomes places competition on native workers, in equilibrium the returns to vacancy creation increases such that firms optimally create more job opportunities. Since natives benefit from this job-creation response, the net effect on native workers is theoretically ambiguous. I show that the net effect of these offsetting forces produces negligible changes to native wages, employment rates, and allocation across firms, both on average and across the skill distribution. This finding is important, as it implies government assistance towards new immigrants does not crowd out or have adverse distributional effects on natives.

Finally, I evaluate the productivity implications of two immigrant integration policies—language training programs (LTPs) and active labor market programs (ALMPs)—which are commonly implemented on a small scale in developed countries. While the evidence suggests these policies are effective at raising immigrant wages and employment in the short term, it is unclear what their long-run or aggregate effects are. By combining causal estimates from the empirical literature and a simulated randomized control trial, I map these programs to the model parameters and find that LTPs and ALMPs improve immigrant outcomes through a combination of increasing immigrant skills and lowering allocative barriers. These effects lead to persistently higher immigrant earnings even 20 years after treatment, partly due to slow baseline assimilation rates and partly because the programs not only shift initial conditions but also increase immigrant incentives for subsequent skill accumulation. A policy where all PRs in Canada are treated by ALMPs would increase immigrant output by almost 8% and total output by more than 1%.

My paper contributes to a large empirical literature on the economics of immigration. Beginning with the seminal work of Chiswick (1978) and Borjas (1985), a substantial literature has shown that immigrants initially earn lower wages than natives and narrow this gap over time.[1] Inspired by a growing literature documenting that the sorting of workers across firms is important for understanding wage inequality (e.g., Card *et al.* (2016); Gerard *et al.* (2021)), recent work has emphasized that a significant share of immigrant wage inequality stems from the types of firms immigrants and natives are employed (e.g., Aydemir and Skuterud (2008); Dostie *et al.* (2023)). As with wages, this sorting gap then closes over time as immigrants climb into higher paying firms (e.g., Arellano-Bover and San (2023); Lehrer and Rawling (2025)). While this literature has provided important descriptive analysis characterizing immigrant inequality, it is largely silent about its causes, making actionable policy recommendations challenging. Conversely, another strand of the literature identifies the short-term, local effects of specific barriers leading to economic disadvantages for immigrants, such as occupational barriers, language barriers, and discrimination (e.g., Oreopoulos (2011); Lochmann *et al.* (2019); Imai *et al.* (2019); Brücker *et al.* (2021); Foged *et al.* (2024a)).

I build on previous empirical work by providing a detailed comparison of how immigrants and natives differ in labor allocation patterns. My dataset allows me to examine immigrant-native gaps in transition rates, both over time and across the firm productivity distribution, and further document the types of firms immigrants move into (and out of), uncovering previously unexamined differences in sorting patterns. These observable patterns shed light on the mechanisms leading immigrants to sort into lower productivity firms and also facilitate identification of the structural model. I then use the model to decompose the sources of immigrant-native inequality assess the aggregate implications of immigrant integration policies, including spillover effects and potential adverse effects on natives, which is infeasible without a general equilibrium framework.

My work also compliments other structural models studying immigration. Much research has examined the impact of immigrants on the host economy, but typically focuses on the effects of immigrant-induced labor supply shocks.[2] Relatively less work has studied the challenges immigrants face upon entering the labor market, the dynamics of how these challenges are overcome, and their broader implications for host economies. Two exceptions are Adda *et al.* (2022) and Albert *et al.* (2021). As in their models, I allow for the fact that not all of an immigrant's human capital is immediately portable across countries and that they may accumulate host-country specific skills, resulting in wage assimilation. However, my model is the first to explicitly incorporate the

[1] See Rho and Sanders (2021) for recent evidence in the U.S. context, Adda *et al.* (2022) for Germany, and Lehrer and Rawling (2025) for Canada. See also Brell *et al.* (2020) for a comparative analysis across Canada, Australia, Denmark, Finland, Norway, Sweden, Germany, the United Kingdom, and the United States.

[2] E.g., see Llull (2018); Monras (2020); Burstein *et al.* (2020); Piyapromdee (2021); Albert and Monras (2022); Brinatti (2024); Terry *et al.* (2024); Brinatti and Morales (2025)

barriers immigrants face in forming employment relationships and sorting across heterogeneous firms, allowing me to make the distinction between human capital and allocational barriers.[3] My work closely relates to Birinci *et al.* (2025), who model barriers to immigrant labor allocation in a static occupational choice framework, focusing on wedges that distort the allocation of immigrant labor across occupations. I instead study allocation across heterogeneous firms within a dynamic search model, where the sources of misallocation are explicitly micro-founded by differences in human capital, search frictions, job instability, and networks that induce differential access to job information. I further add to Birinci *et al.* (2025)'s analysis by capturing the dynamic process through which these barriers evolve as immigrants assimilate.

Finally, I contribute to the literature that uses labor market search models with two-sided heterogeneity to study wage inequality and worker sorting patterns (e.g., Postel-Vinay and Robin (2002); Cahuc *et al.* (2006); Lise *et al.* (2016); Bagger and Lentz (2019)). I innovate on previous work by explicitly incorporating referral networks and endogenous immigrant assimilation into a random search model with two-sided heterogeneity and sorting.[4] There is extensive evidence that a large share of jobs are obtained through referral networks and that these networks are segmented by ethnicity (Topa (2011)). I show that, beyond being consistent with the data, this network structure of the labor market amplifies inequality between immigrants and natives. In my framework, the job opportunities of a worker partially depend on the employment distribution of their network, delivering a novel micro-foundation for observed sorting differences between immigrants and natives.

The remainder of the paper proceeds as follows. In section 2, I describe the Canadian matched employer-employee data and document how immigrants differ from natives in the labor market. In section 3, I describe the structural model. In section 4, I discuss identification of the model parameters, estimate the model, and present the fit to the data. In section 5 I use the model to study the sources of immigrant-native inequality, quantify implications for aggregate output, and evaluate integration policies. Section 6 concludes.

2 Empirical Findings on Immigrants in the Labor Market

In this section, I explore how immigrant workers navigate the labor market, focusing on how they differ from natives and how these gaps evolve as immigrants spend time in the host economy. These findings shed light on how immigrant integration barriers manifest in observable labor market

[3] See also Bowlus *et al.* (2016), who consider immigrant assimilation in search technology but abstract from heterogeneity in worker productivity.

[4] For models with referral networks without productivity heterogeneity in both workers and firms, see Galenianos (2014); Galeotti and Merlino (2014);Dustmann *et al.* (2016); Moon (2023));Arbex *et al.* (2019); Chassamboulli and Peri (2020);Galenianos (2021); Lester *et al.* (2021). These models also typically assume a single undifferentiated network, overlooking systematic differences in job information between segmented groups.

outcomes and facilitate the development and estimation of the structural model described in the following section.

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 data covering the universe of workers and firms in Canada from 2001-2019. This dataset links each worker's Record of Employment (ROE) with their individual tax form (T4) and their employer's tax records. The linked T4-ROE provides employment histories for each worker including firm identifiers, annual employee income at each job, and start and end dates at monthly frequencies. Other key variables, used throughout the analysis as controls, are the firm's industry (2-digit NAICS) and the worker's age, sex, and province of residence. I normalize all nominal income variables to 2012 Canadian dollars.

This dataset is then linked to Canada's Longitudinal Immigration Database (IMDB), which allows me to identify immigrant workers in the tax records, their country of origin, landing date, history of temporary permits, and channel of entry. This comprehensive coverage of matched employer-employee tax data merged with detailed characteristics on the universe of immigrant workers is noteworthy as much of the previous literature on immigrant assimilation relies on observing how the wages of a cohort of immigrants evolves over a series of cross-sections (e.g., Borjas (2015); Albert *et al.* (2021)), or else has a short time horizon or less coverage (e.g., Rho and Sanders (2021); Battisti *et al.* (2022); Adda *et al.* (2022)).

Immigrant workers in Canada arrive as either Permanent Residents (PRs) or on a temporary permit. PRs are workers who migrated from abroad and have been granted permanent access to live and work in Canada. While there are dozens of channels through which an immigrant may obtain PR status, these can be broadly summarized by three main classes: 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. Typically, immigrants entering through family or refugee channels are not evaluated by Canada's point system. Though the proportions vary by year, about 50-60% of PRs enter through the economic channel, 20-30% through the family channel, and the remaining 10-15% are granted PR status as a refugee or on other humanitarian grounds.[5] Canadian PRs also come from a diverse set of origin countries. As of

[5]Statistics Canada. Table 43-10-0026-01 Income of Immigrant tax-filers, by immigrant admission category and tax

2021, about 27% of PRs were from the U.S. or Europe, 51% from Asia, 11% from Latin America and Caribbean, and 10% from Africa.[6] Importantly, PRs are granted the same labor market rights as Canadian citizens, including free mobility across firms. This unrestricted labor market access is unlike, for example, the H1-B program in the United States, where permission to work is often tied to a sponsoring firm.

In contrast, workers on temporary permits, such as work or study permits, are individuals who are granted permission to live, work, and/or study in Canada for a prespecified duration. These workers may be bound to a sponsoring firm and may also face restrictions on the number of hours they can work. Since only about 10% of Canadian immigrants are temporary, and due to the job mobility and hours restrictions often inherent with temporary permits, I focus on PRs for all of the subsequent analysis.[7] In many cases, immigrants first come to Canada on a temporary permit and later transition to PR status. I include these workers in the sample starting from their landing year (the year they become PRs).

I restrict attention to individuals aged 25-65 who never have more than two consecutive years without reported T4 income to focus on workers with a strong attachment to the labor market and who are unlikely to still be in school. Throughout, I follow Adda *et al.* (2022) by defining immigrants as PRs who landed at age 16 or older, grouping PRs who landed as children with native workers.[8] If a worker holds multiple jobs concurrently, I focus on the worker's main job which I define by highest monthly earnings. I employ a similar sample restriction as Bagger and Lentz (2019) and only consider firms that hired at least one worker out of unemployment and one worker from another firm over the sample period. This restriction focuses the analysis on firms that are active in the labor market (rather than sole proprietorships) and reduces noise when we later rank firms by worker flows (Section 2.2). For consistency, I impose this condition throughout all of the empirical analysis and the model simulations. Where start and end dates are missing from the T4-ROE, I impute following a procedure similar to Castro *et al.* (2024) and then verify that neither the share of immigrants nor the immigrant-native gaps in labor market outcomes are driven by this imputation procedure; see Appendix A.1 for more details and discussion.

Table 1 presents observation counts for the final sample. In total there are about 183 million observations with 18.3% coming from immigrant workers. I exploit this full sample to empir-

year, for Canada and provinces, 2022 constant dollars.

[6] Statistics Canada, Census of Population, 2021.

[7] The main programs admitting new temporary workers, the Temporary Foreign Worker Program (TFWP) and International Mobility Program (IMP), have rapidly evolved over the last two decades, with temporary workers making up an increasing share of the Canadian labor force (O'Donnell and Skuterud (2022)). However, the most dramatic shifts in temporary worker admissions occurred in the post-Pandemic period (2021 onwards). In our sample from 2001-2019, temporary workers make up only about 10% of immigrant observations and 2% of total employment.

[8] Although immigrants who land as children may still face challenges, they will have had time in Canadian institutions prior to entering the labor market. The evidence suggests that immigrants who arrive before age 16 are very comparable to native workers in the labor market (see Kerr *et al.* (2024))

Table 1: Observation Counts of Main Samples

	Time period	Total	Native	Immigrant	Immigrant Share
Full Sample	2001-2019	182,821,790	149,348,420	33,473,370	0.183
Model Sample	2010-2019	101,620,900	81,682,400	19,938,500	0.196

Notes: Data is taken from Canadian matched employer-employee administrative data (BEAM). Observations are at the worker-firm-year level. Samples have been restricted to Canadian citizens and permanent residents aged 25-65 who never have more than two consecutive years without T4 labor income. Immigrants are defined as permanent residents who landed at age ≥ 16. All other workers are labelled as native.

ically document a longer time horizon of immigrant assimilation in wages and firm types. For the remainder of the empirical analysis and the model estimation we will focus on the 2010-2019 time period. In this sample, we have just over 100 million observations with 19.6% coming from immigrant workers.

2.2 Motivating fact: Immigrant-native earnings and firm sorting inequality

To document how immigrants differ from natives in some labor market outcome y and how that inequality evolves over time, I estimate the following regression

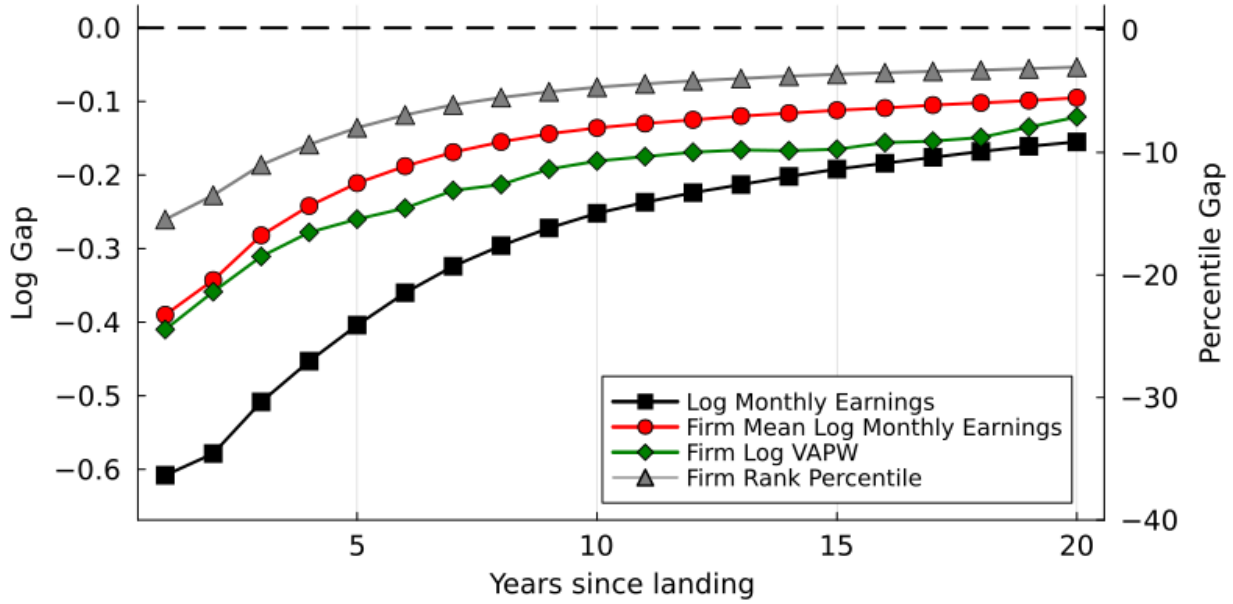
$$y_{ijt} = \beta_{1i} Imm_i + \sum_{\ell=2}^{L} \beta_\ell \mathbf{1}\{YSL_{it} = \ell\} + X_{ijt}\gamma + \epsilon_{ijt}, \tag{1}$$

where y_{ijt} is some outcome variable for individual i employed at firm j in year t, $\beta_{1i} Imm_i$ is an individual fixed effect interacted with an immigrant dummy, YSL_{it} gives the number of years the immigrant has been a landed permanent resident, and X_{ijt} contains fixed effect controls. In the baseline specification, X_{ijt} includes time, province, age, and sex fixed effects.[9] The coefficient β_{1i} captures the initial gap for each immigrant worker relative to the average comparable native, and the coefficients β_ℓ indicate the average amount by which this gap closes ℓ years after landing.

Equation (1) is analogous to the specification used in Chiswick (1978), with the key difference that in Chiswick (1978) the initial immigrant effect is common for all workers ($\beta_{1i} = \beta_1$). As pointed out by Borjas (1985), there are plausible compositional changes in immigrant characteristics across years-since-landing bins—such as those induced by selective out-migration, selective entrance to the labor market, or changes in immigrant cohorts over time—that can confound the estimated assimilation profile used by Chiswick (1978). To overcome this issue, equation (1) exploits the panel nature of the Canadian tax records and focuses on within-worker changes to avoid the

[9]The Canadian administrative data does not provide information on workers' education. Because immigrants in Canada are more likely than natives to hold a bachelor's degree or higher (see Schimmele and Hou (2024)), comparisons between immigrants and natives necessarily reflect, in part, differences in educational attainment.

Figure 1: Immigrant Assimilation in Monthly Earnings and Firm Productivity



Notes: Coefficient estimates are from regression (1) using the BEAM data from 2001-2019. Square markers plot estimates of the immigrant-native gap in log monthly earnings by the number of years since the immigrant became a permanent resident (landed). Diamond markers report gaps in log value added per worker (VAPW) at the current employer. Circle markers report gaps in the mean log monthly earnings at the current employer. Triangle markers plot gaps in the current employer's poach rank percentile. All immigrant-native gaps in outcomes are conditional on age, sex, province, and year.

assimilation parameters β_ℓ being driven by level shifts in mean immigrant outcomes across years-since-landing bins. A similar approach to estimating immigrant assimilation is adopted by Rho and Sanders (2021), and I refer to Appendix A.2 for more discussion and robustness to alternative approaches.

Figure (1) plots assimilation estimates of log monthly earnings based on equation (1) (square markers). I find that immigrants earn 61 log points less than comparable natives in their first year as a PR, closing this gap to 25 log points 10 years after landing and 15 log points 20 years after landing.[10] Immigrants therefore arrive with substantially lower earnings than the average native, but also experience faster earnings growth, especially in the first 5 years after arrival, such that this gap is roughly halved after 8 years.

The remaining lines highlight that immigrants not only earn lower wages, but also work in very different types of firms. I compare immigrants to natives in terms of their employer's average

[10]Since the initial gap in equation (1) is individual specific, the average level of the immigrant-native wage gap is not identified. I therefore normalize the initial gap such that the implied gap in year $\ell = 10$ is to equal the conditional gap for immigrants in that years-since-landing bin. This normalization is innocuous since for most labor market outcomes the within-worker assimilation profile is similar to the assimilation profile implied by the series of conditional gaps, indicating that compositional biases are likely not a large issue in the Canadian data (see Appendix A.2).

pay, value-added per worker, and a revealed preference ranking based on worker flows, following Bagger and Lentz (2019).[11] To rank firms by revealed preference, for each firm j I calculate the total number of new hires coming from unemployment N_j^{UE}, the total number of new hires coming directly from other firms N_j^{EE}, and calculate the firm's "poach share" as

$$PoachShare_j = \frac{N_j^{EE}}{N_j^{UE} + N_j^{EE}}. \tag{2}$$

The intuition is that any voluntary employment-to-employment (EE) transition between two firms reveals the poaching firm to be preferred by the worker. As Bagger and Lentz (2019) point out, binning firms into quantiles based on $PoachShare_j$ provides a model-consistent ordinal ranking of firms by productivity for the class of model I will present in the following section. Moreover, since this method of ranking firms relies on observed worker flows rather than wage or output data, it captures common preferences for non-pecuniary amenities and allows one to rank firms separately for immigrants and natives—a feature I will exploit in the following subsections.

I find that when immigrants first arrive they work at firms with mean log pay 39 log points lower (circle markers), value-added per worker 41 log points lower (diamond markers), and poach rank 17 percentiles lower (triangle markers). As with the gap in log monthly earnings, these gaps close to about one-quarter of their initial value by 20 years in Canada.

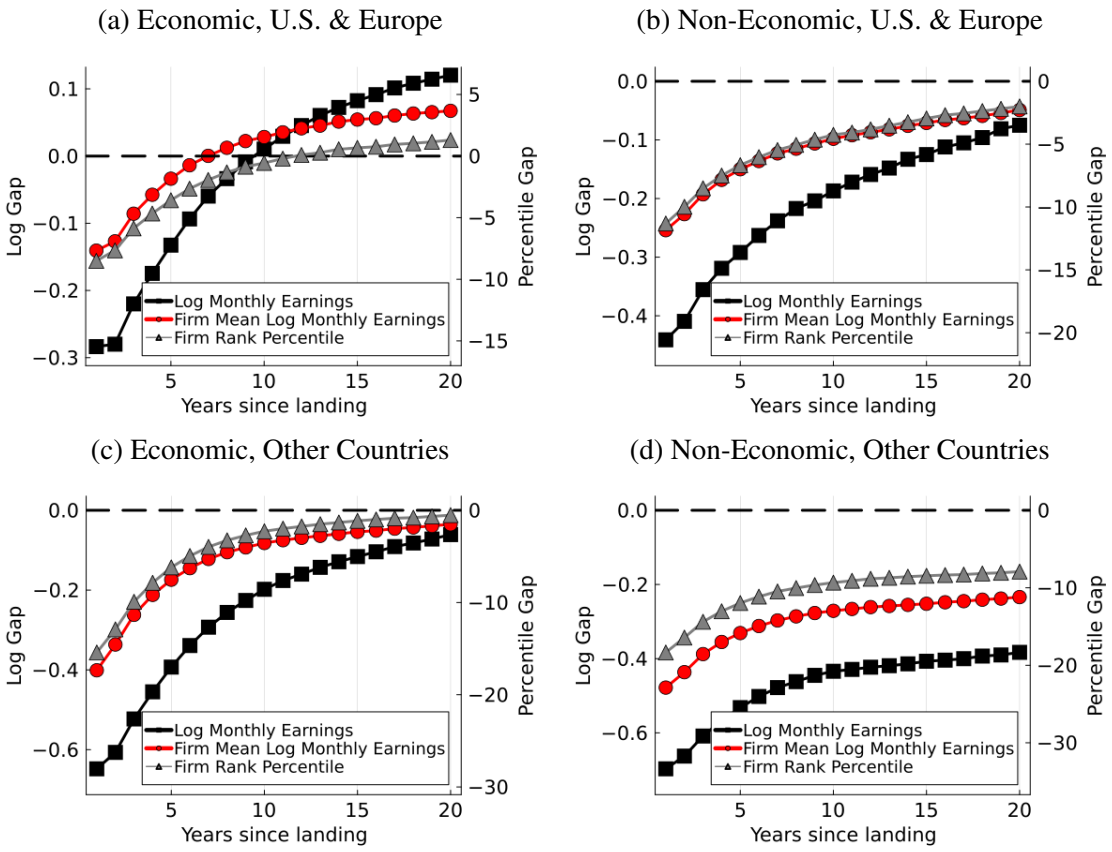
In Figure (2) I repeat this analysis, comparing immigrants from the U.S. and Europe versus other origin countries, and immigrants arriving through one of Canada's economic channels versus through family or refugee channels. Immigrants from the U.S. and Europe are more likely to have similar institutions, language, and culture as Canada, and therefore we would expect them to face less challenges in the labor market. Similarly, since economic immigrants are selected on the basis of their observable human capital such as education and language ability, we would expect them to perform better in the labor market than non-economic immigrants. This intuition bears out in the data: non-economic immigrants and those from countries outside of the U.S. and Europe have the largest gaps in earnings and firm types. Nevertheless, all groups experience initial gaps in earnings and firm types and faster growth relative to comparable natives.

2.3 New facts on immigrant labor allocation patterns

The previous section established that immigrants disproportionately sort into lower-paying, lower-productivity firms, but did not identify the mechanisms driving this outcome. This section takes a first step toward understanding this inequality by analyzing differences in labor market dynamics

[11] See Lehrer and Rawling (2025) for a comparison using the employer's pay premia in the tradition of the Abowd *et al.* (1999) wage model.

Figure 2: Wage and Firm Type Assimilation, by Immigrant Subgroup



Notes: Coefficient estimates are from regression (1) using the BEAM data from 2001-2019. Each panel compares one subgroup of immigrants to all native workers. All immigrant-native gaps in outcomes are conditional on age, sex, province, and year. Square markers plot estimates of the immigrant-native gap in log monthly earnings by the number of years since the immigrant became a permanent resident (landed). Circle markers report gaps in the mean log monthly earnings at the current employer. Triangle markers plot gaps in the current employer's poach rank percentile.

between immigrants and natives, with an emphasis on how immigrants transition between firms and into and out of employment. I then use these dynamics to estimate a structural model that formalizes their implications for immigrant–native wage inequality and the aggregate economy.

I define a labor market transition as an event when (i) a worker changes their main employer, identified by the firm's ID, (ii) does not return to that employer in the following tax year, and (iii) for firms with greater than 10 employees, less than half of the origin firm's employees make a transition to a common destination firm. The latter restriction is intended to capture changes to firm ID stemming from mergers and acquisitions and exclude these from our definition of job transitions. An employment-to-employment (EE) transition occurs when the gap between ending a job and starting the next one is less or equal to one month, an employment-to-unemployment (EU) transition occurs when the gap exceeds one month, and an unemployment-to-employment (UE) transition occurs when a job is subsequently found after an EU transition. I define an unemploy-

ment spell as the duration of time between an EU and UE transition.[12] Although previous work has documented that immigrants differ from natives in labor market transition rates (e.g., Albert *et al.* (2021)), doing so using rich administrative data where one can observe how these relationships vary across time, the firm distribution, and immigrant groups is new.

2.3.1 Fact 1: Immigrants experience higher job instability

I start by considering how immigrants and natives differ in EE and EU transitions. For each worker i employed at firm j at time t, I let the indicator d_{ijt}^{EE} (d_{ijt}^{EU}) be equal to one if the job ends in an EE (EU) transition within the next 12 months and zero otherwise. To calculate annual transition rates for native workers, I simply take the mean of this indicator variable. Native workers have annual EE transition rates of about 0.14 and EU transition rates of about 0.10, implying about one-quarter of native jobs end within the next year. I then estimate immigrant-native gaps using equation (1) with d_{ijt}^{EE} and d_{ijt}^{EU} as outcome variables and age, sex, year and province as fixed effect controls, and plot the estimates over the first ten years after landing (Figure 3).

Three findings stand out as we interpret these figures. The first is that new immigrants have substantially higher job turnover, with about 70% higher EE transition rates and 100% higher EU transition rates than comparable native workers (Figures 3a and 3b). The second finding is that these gaps are short-lived, closing to half by 3-4 years in Canada and almost completely closing by 10 years. These patterns are qualitatively similar across immigrant subgroups; however, immigrants from countries other than the U.S. or Europe tend to have the largest gaps, with economic immigrants having the highest EE rates and non-economic immigrants having the highest EU rates (Figures 3c and 3d).[13]

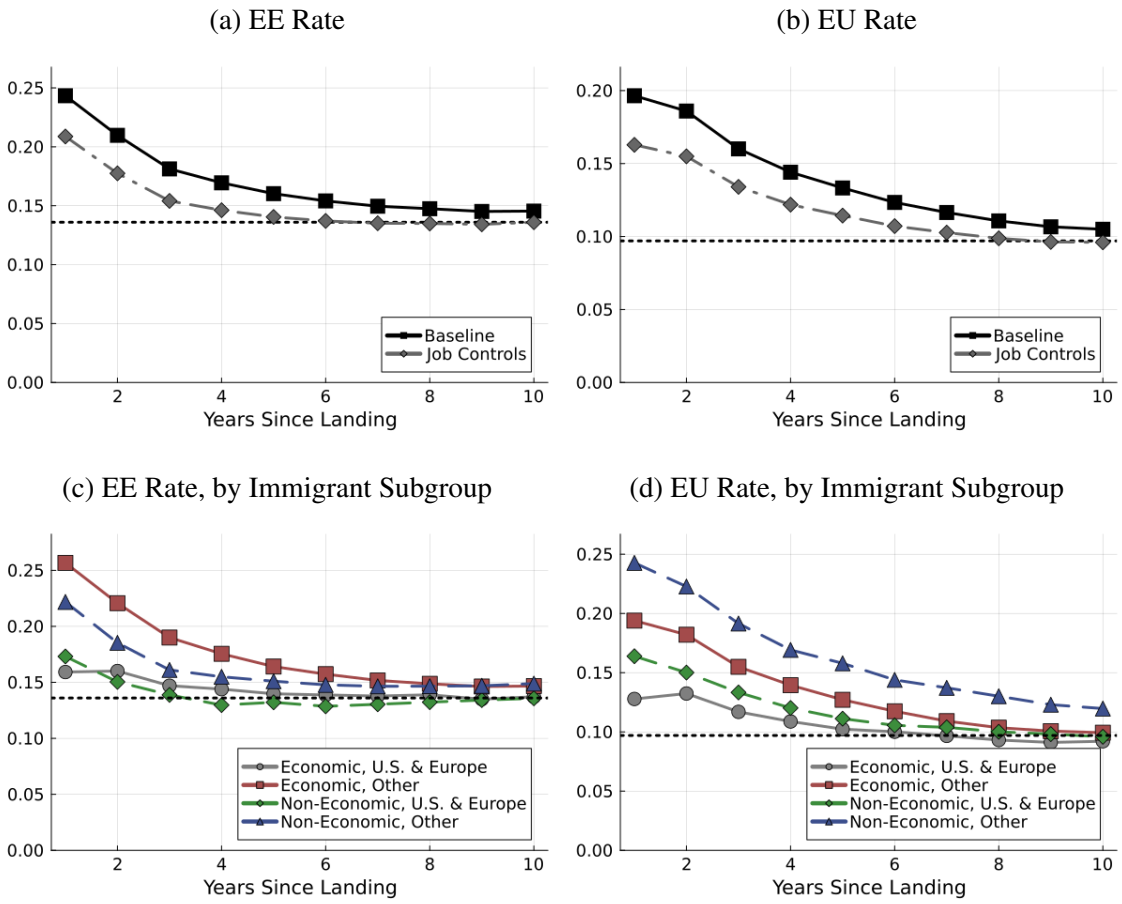
The third notable feature is that much of the immigrant–native gap in EE and EU transitions rates remains even after adding detailed job-level controls. The dashed line with diamond markers adds fixed effects for the firm's industry, percentiles in the firm's poach rank, mean wage, and employment size, and the worker's pay decile within the firm.[14] Relative to natives in similar jobs with similar pay, immigrants in their first year as a PR still exhibit about 50% higher EE and EU rates, suggesting the immigrant-native gaps in transition rates are not entirely driven by immigrants sorting away from lower-paying or lower-productivity firms, nor by immigrants disproportionately

[12] While gaps between job spells may include other reasons for non-employment, such as maternity leave or illness, the sample restrictions exclude workers with extended non-employment spells to avoid such workers driving mean unemployment durations. I find that the mean unemployment duration implied by the administrative data is 7.3 months, which is slightly longer but comparable to estimates from Canada's Labour Force Survey of about 4.5-6 months over the same time period (Statistics Canada. Table 14-10-0057-01 Duration of unemployment, annual).

[13] See Figure A3 for the robustness of these patterns to alternative assimilation specifications, using only transitions between observations with non-imputed job spells, and when ranking firms by wages instead of poach share.

[14] Conditional on the other firm controls, I view the worker's pay position within the firm as a rough proxy for the skill-level of their occupation, which is unobservable in the Canadian data.

Figure 3: Immigrant assimilation in EE and EU Transition Rates



Notes: Coefficient estimates are from regression (1) using the BEAM data from 2010-2019. The y-axis indicates the fraction of employed workers who transition EE (EU) in the next 12 months. Landing year refers to the year the immigrant became a PR in Canada. The Baseline gaps condition on age, sex, province, and year fixed effects. Flat dashed lines indicate the native mean. Job controls add fixed effects for industry, percentiles in mean firm log earnings, percentiles in firm employment size, percentiles in firm poach rank, and deciles for workers pay position within the firm. Bottom panels repeat the baseline analysis by immigrant subgroup.

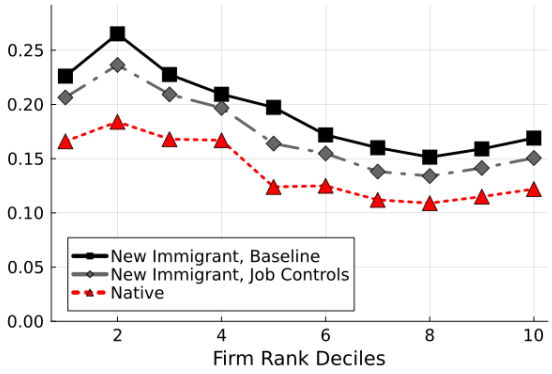
working in sectors with inherently high turnover rates.

To dive deeper into immigrant allocation patterns, I explore the types of firm immigrants are transitioning away from (origin firm) and towards (destination firm), comparing native workers and new immigrants (PRs landing ≤ 5 years ago). The red triangle markers in Figures (4a) and (4b) plot native transition rates conditional on the origin firm's poach rank decile, showing that annual transition rates are highest out of lower rank firms (about 0.17 for EE and EU) and then decline as one moves into higher rank firms (about 0.12 for EE and 0.06 for EU). The difference between the black square markers and the red triangle markers reports the gap between natives and new immigrants, conditional on baseline fixed effects. New immigrant transition rates are shifted up by about 0.05-0.08 across every firm rank decile for both EE and EU transitions, highlighting that new

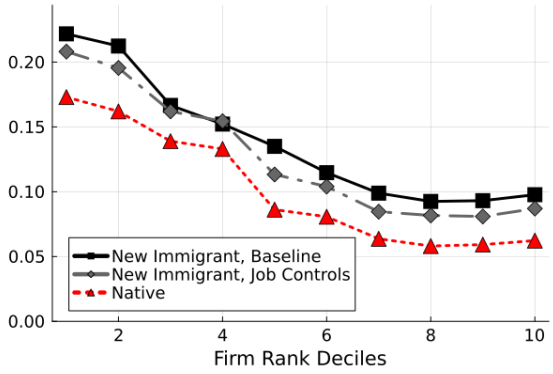
Figure 4: Transition rates and destination firm probabilities, conditional on origin firm rank decile

Annual transition rates, conditional on origin rank

(a) EE Rate

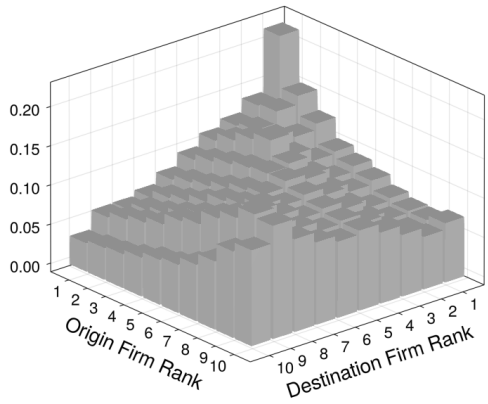


(b) EU Rate

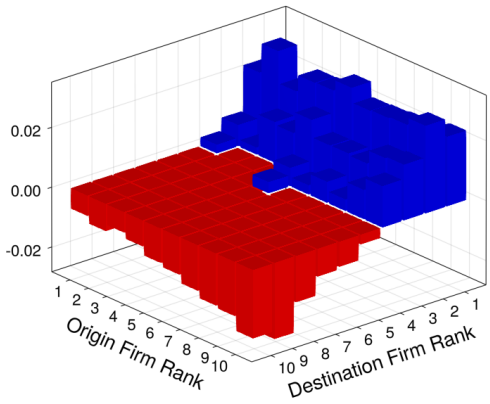


Destination rank transition probabilities, conditional on origin rank

(c) Natives



(d) New immigrants relative to natives



Notes: New immigrants refer to PRs landing five or less years ago. Baseline immigrant-native gaps condition on age, sex, province, and year fixed effects. Job controls further add fixed effects for industry, percentiles of the firm's mean monthly pay and employment size, and deciles for the worker's pay position within the firm.

immigrants are not simply transitioning away from lower rank firms, but rather have systematically higher transition rates across the firm distribution.

Finally, conditional on an EE or EU transition, immigrants tend to move into lower rank firms. Figure 4c plots, for native job movers, the distribution of the destination firm's poach rank decile conditional on the origin firm's poach rank decile. Conditional on transitioning out of a low rank firm (decile 1), native workers are most likely to move into another low rank firm (22% to decile 1) and least likely to move into a high rank firm (3.5% to decile 10). In contrast, native workers in a high rank firm (decile 10) are more likely to move into another high rank firm (12% to decile

10) and less likely to move into lower rank firms (7.5% to decile 1). Figure 4d then shows the *difference* in transition probabilities between natives and new immigrants, where red bars correspond to negative values and blue bars to positive values. There is a clear pattern: conditional on changing jobs, immigrants systematically move into lower rank firms. For example, conditional on transitioning out of a high rank firm (decile 10), new immigrants are 6.4pp less likely than natives to move to a firm with poach rank decile $\geq$ and 7.1pp more likely to move to a firm with poach rank decile ≤ 3.

The transition patterns documented in this subsection point to immigrants experiencing an initial phase of higher job instability. Immigrants exhibiting higher transition rates is not surprising given that they initially sort into lower rank firms and then move upwards (Figure 1). But a closer inspection of immigrant mobility reveals patterns inconsistent with immigrants simply sorting away from lower rank firms and moving up the firm ladder; new immigrants are also more likely than natives to transition away from high productivity firms. Moreover, conditional on moving, new immigrants are more likely to transition back down the firm ladder and into unemployment. These patterns are difficult to rationalize with only voluntary transitions, and instead suggest that some of the high job mobility among new immigrants could be involuntary.

2.3.2 Fact 2: Immigrants face challenges to job finding

In an influential field experiment, Oreopoulos (2011) sent thousands of fictitious resumes to real job openings in Canada and found that callback rates fell by 30% when the resume had a foreign-sounding (e.g., Chinese, Indian) name relative to a typically Canadian name. Since this kind of discriminatory hiring practice will impact the job finding rate of immigrants, I next explore how immigrants differ from natives in transitioning out of unemployment.

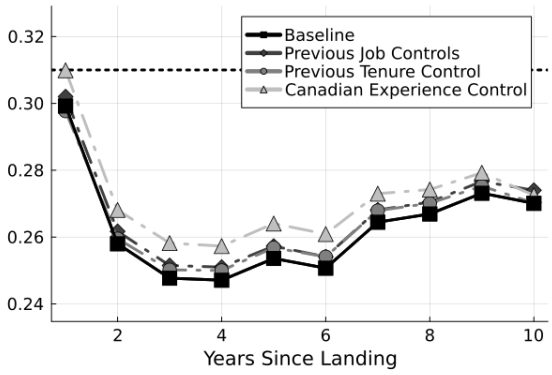
For each worker i who experiences an EU transition out of firm j at time t, I define the indicator variable d_{ijt}^{UE} such that it is equal to one if the worker exits that unemployment spell (experiences a UE transition) within three months. To calculate quarterly UE transition rates, I take the mean of this indicator variable. Native workers have a quarterly UE transition rate of 0.31, implying that about one-third of native unemployment spells end within three months. Figure (5) then plots the immigrant-native gap in quarterly UE rate across years-since-landing bins, estimated from equation (1) using d_{ijt}^{UE} as the outcome variable.

I find that immigrants transition out of unemployment spells more slowly than native workers, but unlike other labor market outcomes the assimilation profile is non-monotonic (Figure 5a). Immigrants who enter unemployment in their first year as a PR have almost the same quarterly UE rate as similar natives; this gap then widens until years 3-4 where immigrant UE transitions rates are about 20% lower than natives, before starting to slowly narrow (black square markers).[15] These

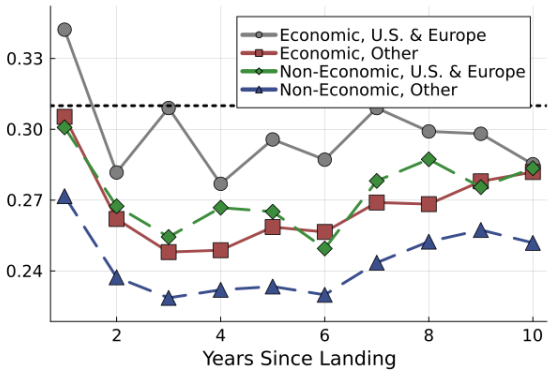
[15]The U-shaped relationship is similar using alternative assimilation regressions and when only looking at transitions

Figure 5: Quarterly UE Transition Rate Assimilation

(a) All Immigrants



(b) By Immigrant Subgroup



Notes: Coefficient estimates are from regression (1) using the BEAM data from 2010-2019. The y-axis indicates the fraction of unemployed workers who found a new job within three months of entering unemployment. The flat dashed line indicates the mean among native workers. Square markers in panel (a) report immigrants relative to natives conditional on age, sex, province, and year. Diamond markers add controls for the job held prior to separation, including fixed effects for industry, percentiles in mean firm log earnings, percentiles in firm employment size, percentiles in firm poach rank, and deciles for workers pay position within the firm. Circle markers control for tenure fixed effects at the previous firm before separation. Triangle markers replace age fixed effects with potential Canadian experience, defined as time since age 25 for natives and the minimum of time since landing and time since age 25 for immigrants. Panel (b) repeats the baseline analysis separately by immigrant subgroup.

patterns are qualitatively the same for across immigrant subgroup, but the gaps are quantitatively driven by non-economic immigrants and by immigrants from countries other than the U.S. or Europe (Figure 5b).

Part of the gap in job finding rates could be driven by immigrant-native differences in skills, since job finding rates may be lower for lower-skill workers. To explore this possibility, the remainder of the lines in Figure (5a) add additional fixed effect controls to the baseline specification, showing that these lower UE transition rates are hard to account for with worker or firm observables. The line with diamond markers conditions on characteristics of the worker's most recent job, including fixed effects for the firm's percentile in poach rank, mean wage, and employment size, the firm's industry, and the worker's pay decile within the firm. The estimates are nearly identical with these controls, showing that the UE transition rate gaps persist among workers who previously held jobs in similar firms and sectors and who had similar monthly earnings. The line with circle markers conditions on the worker's job tenure before the EU separation, and the final line with triangle markers replaces the age fixed effects with fixed effects for potential Canadian experience.[16]

between jobs with non-imputed start and end dates (Figure A2a). A similar (inverted) U-shape pattern also arises when looking at unemployment duration rather then transition rates (Figure A2b). Further, these patterns are the same when looking at male and female workers separately (Figure A2c), suggesting other absences such as maternity leave are not driving the gaps.

[16] I define potential Canadian experience as the time since landing for immigrants and time since age 25 for natives.

Again, these controls hardly shift the assimilation estimates, suggesting that immigrants with the same previous job tenure and potential experience as natives still exit unemployment more slowly.

In the model, I will allow for immigrant-native job finding rates to differ from both differential search effort and differences in worker skills, but will ultimately find that barriers to job search, such discriminatory hiring practices or slow recognition of foreign credentials, are required to account for these patterns.[17] This structural result is consistent with the empirical evidence, since additional controls that strongly correlate with worker skills do not explain UE transition rate gaps and existing survey evidence shows new immigrants search at least as intensively for work as natives (e.g., see Carlsson *et al.* (2018)).

2.3.3 Fact 3: Ethnically segmented referral networks

A final reason immigrants may experience difficulty sorting into higher-rank firms relative to native workers is the network of contacts immigrants have access to. Survey data typically finds that around half of all jobs are found through personal contacts (Topa (2011)), and that these networks tend to be segmented along ethnic lines. For example, the Longitudinal Survey of Immigrants to Canada (LSIC) surveyed a cohort of new immigrants who landed in Canada between 2001-2002 and showed that 44% of all jobs held in the first four years were found through personal contacts and that almost 90% of these contacts were either a family member or a friend of the same ethnicity. Importantly, the vast majority of these immigrants did not have jobs lined up prior to arrival, implying that these patterns are the result of labor market search within Canada. This segmentation of referral networks has the potential to amplify inequality since the employment distribution of a workers personal contacts partially dictates the distribution of jobs available to that worker, and we have already seen that immigrants are largely allocated into lower-paying, lower-productivity firms.

Co-ethnic referral networks are not directly observed in the administrative data, but will manifest in job flows and hiring patterns. In particular, since incumbent workers at a firm become a source of job information to their co-ethnic contacts, we should observe workers gravitating to firms that have a higher share of incumbent, same-origin workers. I start by looking at how the composition of new hires at a firm varies with the composition of incumbent workers. I define new hires as workers who just made a UE or EE transition into a new firm, and incumbent workers as those who were already employed at the firm last period and remain there this period. For every

Comparing immigrants and natives of the same experience will in general compare older immigrants to younger natives.

[17] The U-shaped pattern in UE transition rates will then arise naturally from the offsetting dynamics of initially high immigrant job search effort and lower job finding rates per unit of search effort; see section 4 for more details.

Table 2: Relationship between ethnic composition of new hires and incumbent workers

	New hires co-ethnic %					
	All		Immigrants			
	(1)	(2)	(3)	(4)	(5)	(6)
Incumbent co-ethnic %	0.597***	0.518***	0.819***	0.469***		0.840***
	(0.000391)	(0.000354)	(0.000790)	(0.000980)		(0.000810)
Incumbent other-ethnic %					-0.0594***	0.0938***
					(0.00118)	(0.00104)
Province and year FE	yes	yes	yes	yes	yes	yes
Country of birth FE	yes	yes	yes	yes	yes	yes
Firm type controls		yes		yes		
Observations	17,322,000	17,322,000	2,260,990	2,260,990	2,260,990	2,260,990
R-squared	0.783	0.826	0.421	0.770	0.094	0.426

Notes: Using BEAM data from 2010-2019. Sample includes workers who just made a UE or EE transition into a new firm in the current year. Immigrants includes workers who landed ≤ 10 years ago. Table reports estimated coefficients γ from regression (3), capturing the relationship between the share of new hires from a given country of origin and the share of incumbent workers from that same country. Columns 1 and 2 include both immigrants and natives, columns 3-6 restrict the sample to only immigrants. Standard errors are clustered at the individual level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

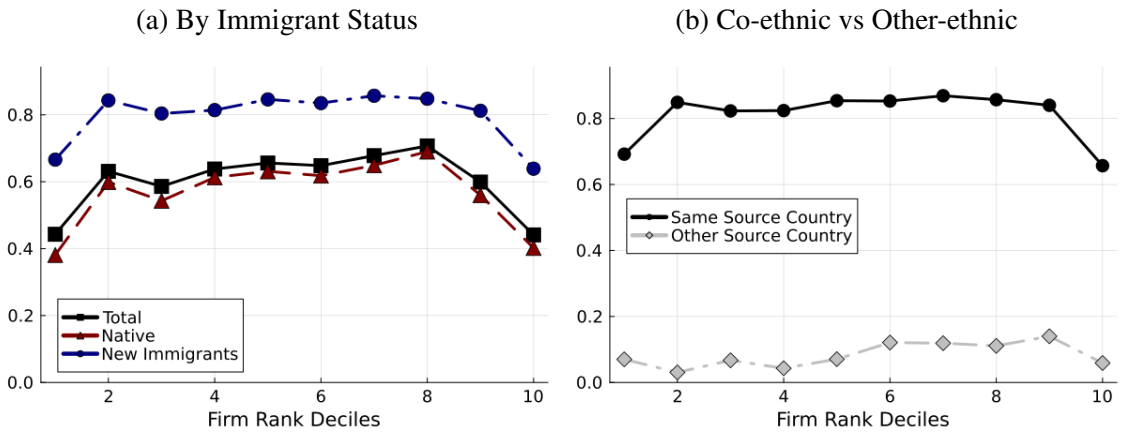
new hire, I estimate the regression

$$s^{New}_{j,C(i),t} = \gamma s^{Inc}_{j,C(i),t} + X_{j,t}\beta + \delta_{C(i)} + \epsilon_{ijt} \tag{3}$$

where $s^{New}_{j,c,t}$ and $s^{Inc}_{j,c,t}$ are the share of new hires and incumbents being from origin c for firm j at time t, $C(i)$ denotes country of origin for worker i, $X_{j,t}$ controls for year and province fixed effects, and δ_c is an origin fixed effect which demeans the shares for each country. The coefficient of interest is γ, which captures the sensitivity of the composition of worker inflows to the composition of incumbents. I focus on natives and immigrants who landed ≤ 10 years ago.

Workers strongly sort to firms with incumbent employees from the same country of origin. Combining native and immigrant new hires, I find that increasing the share of incumbent employees that are from c by 1 percentage point is associated with a 0.60 percentage point increase in the share of new hires from c (Table 2, column 1). This positive coefficient indicates that the employment distribution of co-ethnic workers is a strong predictor of sorting patterns across firms. Restricting the sample to immigrant workers, I find that increasing the incumbent share from country c by 1 percentage point is associated with a 0.82 percentage point increase in the share of new hires from c (column 3), showing that immigrant flows are more responsive to the location of their co-ethnics than native flows. I then add fixed effects for 2-digit NAICS industry and percentiles in the firm's mean monthly earnings, employment size, and poach rank (Columns 2 and 4). The

Figure 6: Co-Ethnic Sorting Across the Firm Distribution



Notes: Using BEAM data from 2010-2019. Sample includes workers who just made a UE or EE transition into a new firm in the current year. Panel (a) reports estimated coefficients γ from regression (3), conditional on the poach rank decile of the hiring firm and splitting the sample into all workers, natives, and immigrants. Panel (b) restricts the sample to immigrants and plots the relationship between new hires and co-ethnic immigrants (circle markers) and other-ethnic immigrants (diamond markers).

coefficient estimates fall to 0.52 in the full sample regression and 0.47 among immigrant workers, suggesting that some of these sorting patterns could be explained by workers of certain origin countries sorting into certain types of jobs. Nevertheless, the majority of these patterns remain even among firms that are observably very similar. Finally, I estimate the relationship between the share of new hires from country c and the incumbent share of *other* immigrant workers, not from country c (columns 5 and 6). The sorting patterns between immigrants from different countries is comparatively much weaker: increasing the incumbent share of immigrants from origins other than c by 1pp is associated with only a -0.05pp to 0.1pp change in the share of new hires from c. The weak sorting patterns between immigrants of different origins suggests the dimension along which immigrants are sorting is ethnicity and not some other factor that affects immigrants collectively.

I next document how these patterns vary across the firm distribution. Figure (6a) plots the estimates from equation (3) conditional on the firm's poach rank decile. We observe strong ethnic sorting patterns across the firm rank decile bins, exhibiting a hump-shaped relationship and ranging from 0.4-0.7. The patterns are qualitatively similar for immigrants and natives, but are stronger for immigrants. I again find a strong gravitation towards co-nationals but a weak gravitation towards other immigrants (Figure 6b), indicating that these sorting patterns are occurring along ethnic lines.

Immigrants may gravitate to each other for reasons other than job finding through networks. Two obvious alternative explanations are preferences and productivity. Immigrants of the same ethnicity may prefer to work together—for example, if having culturally similar co-workers provides utility—and may also share common preferences over job amenities, such as being a close

commute to the neighborhood in which many immigrants of the same ethnicity co-locate.[18] Similarly, immigrants might be more productive in certain types of jobs. This differential productivity could arise from a Roy-style comparative advantage over certain types of tasks, but could also arise if some types of jobs see positive production complementarities in hiring workers from the same origin, such as the benefits of sharing a common language if incumbent workers have low English proficiency.

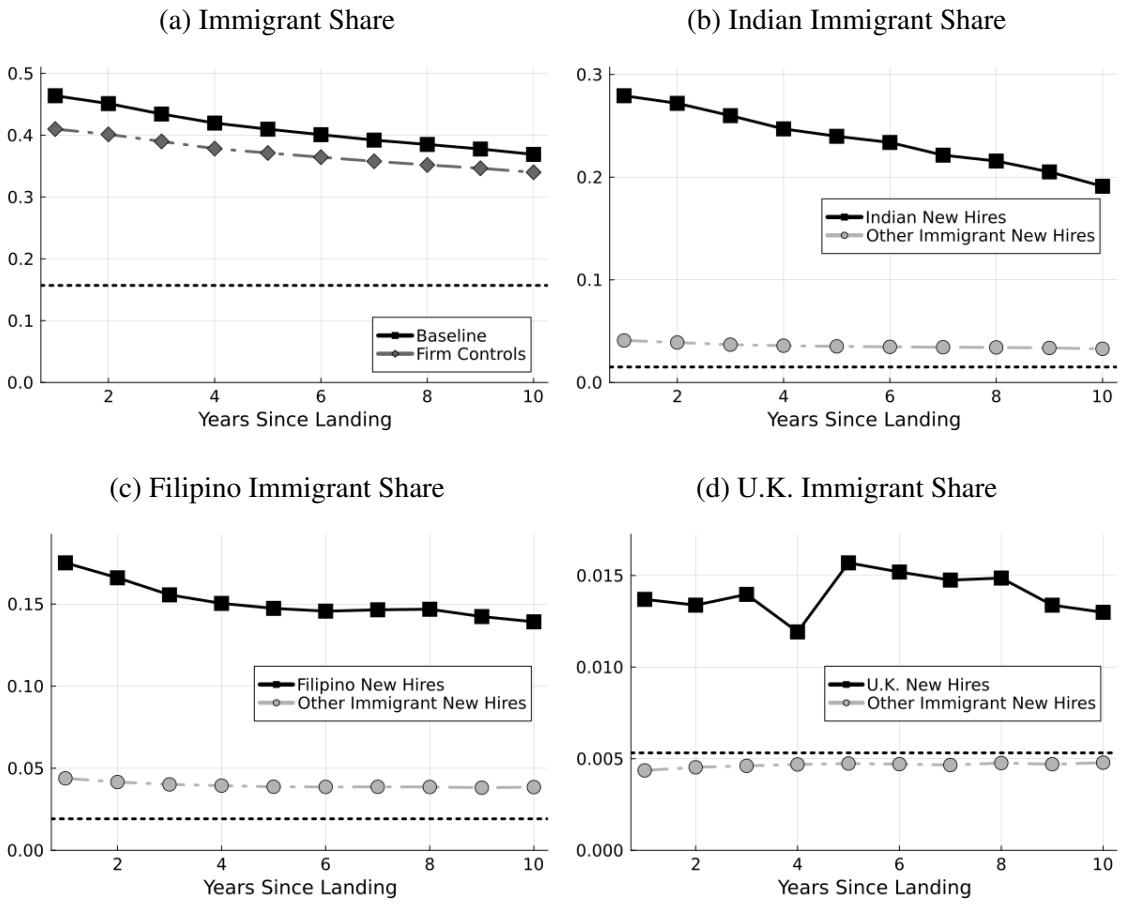
The essence of these competing explanations is that immigrants rank firms differently than natives, either because of preferences or because they are differentially productive, so that the observed sorting patterns are a product of *selection* rather than *information*. To explore whether this is the case, and to evaluate the extent to which this accounts for the above-documented patterns, I re-calculate the firm's poach rank by estimating equation (2) separately for immigrants and natives. Assigning a separate firm ranking for each group allows for the possibility that immigrants systematically prefer, or are more productive in, different types of firms than native workers. Restricting to the set of firms that actively hire both immigrant and native workers, and can therefore be assigned both an immigrant and native ranking, I find that the immigrant and native rankings are positively but imperfectly correlated, with a correlation of 0.5.

To quantify the importance of differential firm rankings for generating the observed sorting patterns, I test whether controlling for the immigrant ranking weakens the ethnic sorting patterns. Controlling for percentiles in the immigrant poach rank reduces the estimated sorting coefficient from 0.83 to 0.76; conditional on the native ranking, the coefficient only falls from 0.71 to 0.69 (Table A3). Figure (A4) similarly plots these estimates across the (original) firm rank distribution and shows that controlling for immigrants firm rank has only modest effects, mostly at the bottom of the firm distribution. These results indicate that while immigrants may rank firms differently than natives, the vast majority of co-ethnic sorting occurs among firms they themselves rank the same, suggesting another mechanism is at work. Moreover, the gravitation towards co-nationals is a phenomenon across all immigrant groups, not just those linguistically or culturally dissimilar to natives. For example, the sorting coefficient is 0.76 for workers from the U.S. and Europe and 0.82 for workers from all other countries, and is strong even for immigrants from the U.S. and U.K. (Table A2). The strong co-ethnic sorting patterns for countries such as the U.S. are inconsistent with such patterns being driven by language or cultural considerations. Taken together, these patterns are more consistent with an information story than with selection, which I will interpret in the structural model as evidence of co-ethnic referral networks transmitting job information through incumbent workers.

Finally, I analyze how these sorting patterns evolve as immigrants spend time in Canada. Taking the set of workers who just transitioned into a new job (new hires), I estimate the assimilation

[18] For evidence that immigrants sort geographically into the same neighborhoods, see for example Edin *et al.* (2003).

Figure 7: Co-ethnic Incumbent Share at Firm Among New Hires



Notes: Using BEAM data from 2010-2019. Sample includes workers who just made a UE or EE transition into a new firm in the current year. Panel (a) plots the incumbent immigrant share at the firm and panels (b)-(d) the incumbent share for specific countries of origin. Flat dashed lines report the native average. Estimated coefficients are from regression (1). Firm controls include fixed effects for industry and percentiles in firm mean log wage, employment size, and poach rank.

regression (1) with the destination firm's incumbent immigrant share as the dependent variable (Figure 7). The dash line reports the average among native new hires, showing that natives typically join firms with about 16% of their workforce being immigrants. The black solid line then calculates the conditional gap in this statistic between immigrant and native workers, showing that immigrants strongly gravitate to firms where there is a high representation of other immigrants. For jobs found in their first year as a PR, the incumbent immigrant share is three times higher than comparable natives, with about 47% of the firm being composed of other immigrant workers. Immigrants then start sorting into firms with a higher representation of native workers over time. For example, immigrants finding a new job 10 years after landing will on average allocate to firms with a 37% share of incumbent immigrants, down 10pp from when they first arrived. Assimilation along this dimension is markedly slower than the rate of assimilation in other labor market outcomes, such

as wages or EE/EU transition rates, suggesting that the process of social assimilation is slow. As before, these patterns persist after controlling for detailed firm controls (gray dashed line), and are largely driven by co-ethnics. For example, among Indian workers (who are the largest immigrant group in Canada), Indian new hires in their first year as a PR sort to firms with almost a 30% share of Indian incumbents, whereas other immigrants and natives sort to firms with only a 4% and 1.5% share of Indian incumbents, respectively (Figure 7b). Similar patterns exist for Filipino immigrants, the second largest origin group in Canada (7c), and U.K. immigrants, one of the largest origin groups among developed, Western countries (Figure 7d).

2.4 Discussion

The substantial immigrant-native gaps in earnings and firm sorting followed by convergence have motivated a vast literature on what accounts for this assimilation process and what its implications are for the host economy. In principle, this entire process could be driven by immigrant-native differences in worker productivity: immigrants may land with lower skills, possibly due to weaker institutions in the origin country or imperfect skill transferability across labor markets, causing them to earn less and optimally settle into lower productivity jobs. Then, immigrants earn more and climb into better firms over time as they acquire the necessary destination-specific skills. While differences in skills almost certainly plays a role in the assimilation process, it is also possible that immigrants face unique labor market barriers that hinder their ability to allocate efficiently across firms. In this case, the observed earnings and firm sorting gaps are not driven solely by skill deficiencies but also by barriers to finding and retaining suitable employment. Since worker ability is unobserved, it is difficult to distinguish between these alternative explanations and therefore difficult to make policy recommendations from Figure (1) alone.

In this section, I explored differences between immigrants and natives in terms of labor market dynamics and job finding patterns, highlighting that immigrants appear to experience higher job instability, face barriers to job finding, and have a different referral network that strongly affects their allocation of labor. I now develop a structural search model of worker sorting, referral networks, and immigrant assimilation that can use this rich set of empirical patterns to disentangle these competing explanations for immigrant-native inequality and explore their implications for aggregate productivity.

3 A Model of Immigrants in the Labor Market

Immigrants differ from natives not only in earnings and the types of firms they work in, but also in the dynamics of how they sort and transition between firms. I now build a general equilibrium

search model with heterogeneous workers and firms that captures these patterns and uses them to better understand the sources of immigrant-native labor market inequality.

Specifically, I extend the environment of Bagger and Lentz (2019) to include (i) distinct worker groups that differ in labor market fundamentals, (ii) dynamic between-group inequality that arises from immigrant workers' assimilation decisions, and (iii) job finding through segmented referral networks. Extensions (i) and (ii) capture the fact that new immigrants differ from natives in the labor market in a variety of ways, but achieve more similar outcomes over time. Extension (iii) is important not only because segmented referral networks are an empirically prevalent method of job finding, but also because they have important implications for how immigrants sort across firms.

3.1 Worker and Firm Heterogeneity

Time is continuous, and all agents discount the future at rate ρ. The economy is populated by a unit mass of heterogeneous workers and a mass N^f of heterogeneous firms. Firms differ in their productivity $p \in [0,1]$, $p \sim L(p)$ and choose how intensively to recruit new workers. Workers are either employed by a firm of type p or else unemployed and choose how intensively to search for work both off- and on-the-job. Workers exogenously exit the labor market at rate d, and are replaced by new entrants such that the economy remains in steady state.[19] A fraction of new entrants $\alpha(o)$ enter the labor market employed by drawing an initial job offer prior to entry, and the remainder enter unemployed. Let $r = \rho + d$ be the effective discount rate.

Workers are heterogeneous in three respects. First, when workers enter the labor market they draw an ability type $x \in [0,1]$ that affects their productivity. Second, workers may differ according to their group $o \in \mathcal{O} \equiv \{0, 1, \ldots, O\}$, where 0 refers to native workers and the rest distinguish between different types of immigrants. Workers of different groups may differ in terms of labor market parameters and their network of personal contacts, allowing for between-group inequality. Finally, workers are also heterogeneous in a K-dimensional state variable $\mathbf{a} \in \mathcal{A} \equiv \{0,1\}^K$, which I refer to as their assimilation status. The main purpose of $\mathbf{a}$ is to distinguish newer from more established immigrants, which will allow the model to capture the empirical pattern that immigrant-native inequality is *dynamic*—in the sense that gaps in observable labor market outcomes tend to close with time in the destination labor market. Native workers are fully assimilated

[19] 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. Two recent developments in this area are Elsby and Gottfries (2022), who develop a model that permits out of steady-state dynamics but requires homogeneous workers, and Lise and Robin (2017), who develop a model that permits aggregate dynamics with two-sided heterogeneity but requires the restriction that workers have no bargaining power, which inherently places restrictions on wage dynamics. Moreover, neither of these frameworks allow for endogenous search intensity. I view worker heterogeneity, endogenous worker decisions, and flexible wage-setting as more central to my research question.

($\mathbf{a} = \mathbf{1}$) by definition, whereas new immigrants arrive in the host country unassimilated ($\mathbf{a} = \mathbf{0}$) with labor market fundamentals that differ from natives in K dimensions. Overtime, immigrants become more like natives along each dimension ($a_k \to 1$), resulting in eventual convergence of labor market outcomes.[20] Once $\mathbf{a} = 1$, immigrants are identical to a native worker of the same productivity type x. The details of this process are explained in section 3.5.

3.2 Job Finding

Workers choose their search effort s subject to an increasing and convex cost function $c_S(s; \mathbf{a}, o)$. Letting $i \in \{0, 1\}$ denote whether the worker is unemployed or employed. The total job finding rate conditional on search effort s is

$$\lambda_i(p, \mathbf{a}, o; s) = \tau_{Si}(p, \mathbf{a}, o)\zeta_i(s)\hat{\lambda}(p, \mathbf{a}, o). \tag{4}$$

The function $\zeta_i(s)$ dictates how search effort s impacts the job finding rate. The function $\tau_{Si}(p, \mathbf{a}, o) \leq 1$—which I refer to as *search barriers*—captures anything that makes it more challenging for immigrants to find employment conditional on their type and search effort. This search barrier will capture discrimination in firms' hiring decisions (see Oreopoulos (2011)) but can also be interpreted more broadly to include other issues that impact immigrants' access to jobs, such as imperfect recognition of formal credentials. I let $\tau_{Si}(p, \mathbf{a}, o)$ depend on firm type p since immigrant-native gaps in job finding rates are largest among transitions into higher productivity firms (section 2.3.2), suggesting search barriers may impact job opportunities more at high-productivity jobs. Immigrant search barriers also depend on the workers assimilation status $\mathbf{a}$ to allow these barriers to dissipate over time—e.g., as immigrant workers obtain credentials in the host labor market. I normalize $\tau_{Si}(p, \mathbf{a}, o) = 1$ for native workers and refer to $\tau_{Si}(p, \mathbf{a}, o)\zeta_i(s)$ as workers' *effective search*. Finally, $\hat{\lambda}(p, \mathbf{a}, o)$ is the equilibrium rate at which a worker finds a type p job per unit of effective search. This function depends on workers' assimilation status $\mathbf{a}$ and origin o in equilibrium to due segmented referral networks which I describe in the following subsection.

3.3 Vacancy Posting and Referrals

Each firm j of type p chooses how many vacancies v to post subject to a per-period vacancy posting cost $c_V(v)$. Meetings between the posted vacancy and potential new hires are generated in one of two ways. First, the firm can wait to meet a worker formally at rate $\lambda^v \equiv \frac{M(N^s, N^v)}{N^v}$, where N^S is the aggregate mass of workers' effective search, N^V is the aggregate mass of posted vacancies,

[20] It is theoretically trivial to allow for an arbitrary number of states between 0 and 1 such that $\mathcal{A} = \{0, 1/n, 2/n, \ldots, 1\}^K$. This leads to $(n+1)^K$ combinations of assimilation status for each immigrant group o. I focus on a binary assimilation status to reduce computational costs in estimation.

and M is the aggregate meeting function. The probability that the meeting is with a worker of subgroup $(\mathbf{a}, o)$ is equal to that subgroup's relative effective search $N^S(p, \mathbf{a}, o)/N^S$.

Second, firms may meet workers through referrals. Workers are connected to a referral network $\mathcal{N}(\mathbf{a}, o)$ that informs them of open vacancies, creating additional meetings between workers and firms. In particular, at rate $\phi\lambda^v$ an incumbent worker at firm j passes information about the vacancy to another worker in their network. A worker's network $\mathcal{N}$ and their group o are tightly linked, but I distinguish between the two to allow for the possibility that a worker's network evolves over time.

In equilibrium, ex-ante identical firms will differ ex-post in the group composition of their workers. Let $\sigma_j(\mathcal{N})$ denote the share of incumbent workers at firm j that belong to network $\mathcal{N}$ and let $\Omega(\sigma|p, \mathcal{N})$ denote the distribution of $\sigma_j(\mathcal{N})$ among type p firms. I assume that referral job information flows out in proportion to the share of workers at the firm, so that the probability that a referral-generated meeting is with a worker from network $\mathcal{N}$ is simply $\sigma_j(\mathcal{N})$. I further assume that firms commit to a hiring strategy upon entering, such that their optimal choice of v depends on their type p but not the current composition of workers at their firm $\boldsymbol{\sigma_j} \equiv \{\sigma_j(\mathcal{N})\}_{\mathcal{N}}$.

The firms' problem is then,

$$\max_{v} \quad v\lambda^v \sum_{\mathbf{a},o} \Big[\underbrace{\frac{N^S(p, \mathbf{a}, o)}{N^S}}_{\text{Formal meetings}} + \underbrace{\phi\bar{\sigma}(p, \mathcal{N}(\mathbf{a}, o))}_{\text{Referral meetings}} \Big] \Pi(p, \mathbf{a}, o) - c_V(v), \tag{5}$$

where $\bar{\sigma}(p, \mathcal{N}) \equiv \mathbb{E}[\sigma|p, \mathcal{N}] = \int_0^1 \sigma d\Omega(\sigma|p, \mathcal{N})$ is the aggregate share of workers employed by type p firms that belong to network $\mathcal{N}$ and $\Pi(p, \mathbf{a}, o)$ is the expected value to the firm of that meeting taking into account the probability that the meeting culminates in a match. Matches form whenever the employment relationship is acceptable to both parties.

There are three substantive assumptions built into equation (5) that dictate how referrals function in the model. First, I assume there is a linear relationship between the share of workers at the firm belonging to some network $\mathcal{N}$ and the probability that a referral reaches a worker from that network. This assumption is key for the model's tractability since referral flows will depend only on the mean share among type p firms $\bar{\sigma}(p, \mathcal{N})$ rather than the entire distribution $\Omega(\sigma|p, \mathcal{N})$. The empirical implication is that the share of new hires from network $\mathcal{N}$ should increase linearly in the share of incumbent workers from that same network. I confirm such a linear relationship holds in the Canadian data comparing the co-national share of new hires to incumbent workers (see Figure A5).

The second important assumption is that ϕ is an exogenous parameter that is constant across firms. While ϕ could easily be allowed to vary across the firm distribution, I show in Figure A6 that there is no systematic relationship between firm productivity and co-national sorting patterns.

As I will show in section 4, the combination of these first two assumptions—linearity and exogeneity—has a further desirable property in that it allows ϕ to be identified reduced-form from the co-national sorting patterns of equation 3.[21]

The final assumption is that the expected value of a meeting $\Pi(p, \mathbf{a}, o)$ is the same regardless of whether the meeting was obtained through the formal or referral channel. This assumption abstracts from the potential for referrals to lead to higher quality matches and therefore lower job turnover. If this match-quality function of referral networks were central, I would expect that, all else equal, workers who move to firms with a higher co-national share—where referrals are more likely to have been used—will have lower subsequent job mobility than when they move to firms with a lower co-national share. I do not find this relationship in the Canadian data (see Figure A7), which justifies this paper's emphasis on the role of networks in creating worker-firm matches.[22]

Therefore, despite it's parsimony, these modeling choices surrounding the role of referrals lead to both tractability and greater transparency in estimation while remaining empirically consistent.

3.4 Wages and Value Functions

Let $V(p, x, \mathbf{a}, o)$ denote the joint value of a match between a type p firm and a type $(x, \mathbf{a}, o)$ worker. Similarly, let $W_0(x, \mathbf{a}, o)$ be the value of unemployment and $W_1(p, w, x, \mathbf{a}, o)$ the value of employment to a worker employed at a type p firm and earning wage w.

Wages. Wages are set following the second-price auction mechanism of Cahuc *et al.* (2006). Therefore, a worker's wage will depend on their type $(x, \mathbf{a}, o)$, their employer's type p, and their ability to command a higher share of the match surplus. The worker's share of the match surplus will in turn depend on their bargaining parameter $\beta(\mathbf{a}, o)$ and outside option at the time of negotiation.

Unemployment value function. When unemployed, workers receive flow value $b(x, \mathbf{a}, o)$. The

[21] In an earlier version of this paper ϕ was an endogenous choice made by the firm at some convex cost. Due to the flat co-national sorting profile across the firm distribution, this made little difference in the counterfactual exercises but added computational burden and reduced transparency in estimation as the referral parameters were no longer identified reduced-form.

[22] Moon (2023) similarly finds that the creation of worker-firm meetings is quantitatively the more important function of referrals.

value function for an unemployed worker is then,

$$rW_0(x,\mathbf{a},o) = \max_{s,\{\eta_k\}_{k\in\mathcal{K}}\geq 0}\Big\{b(x,\mathbf{a},o) - c_S(s;\mathbf{a},o) + \zeta_0(s)\beta(\mathbf{a},o)\int_{\mathcal{R}(x,\mathbf{a},o)}^{1}[V(q,x,\mathbf{a},o) - W_0(x,\mathbf{a},o)]\tau_{S0}(q,\mathbf{a},o)\hat{\lambda}(q,\mathbf{a},o)dq + \sum_{k=1}^{K}\eta_k[W_0(x,\mathbf{a}+\iota_k,o) - W_0(x,\mathbf{a},o)] - \sum_{k\in\mathcal{K}}c_{\eta_k}(\eta_k)\Big\}. \tag{6}$$

The first line denotes the flow value of being unemployed net of search costs. The second line denotes the expected value of future job opportunities conditional on search effort s. Unemployed workers who find a job accept if the firm is above their reservation cutoff $\mathcal{R}(x,\mathbf{a},o)$. The final line represents the value from immigrant assimilation, which I expand on in the following subsection.

Match value function. Once matched with a firm of type p, the worker and firm generate flow production $f(p,h(x,\mathbf{a},o))$, where $h(x,\mathbf{a},o) = \tau_h(\mathbf{a},o)x$.[23] Here, x should be viewed as the worker's *innate* skill type and $h(x,\mathbf{a},o)$ as their skill *effective* in production. I normalize $\tau_h(\mathbf{a},o) = 1$ for native workers, so that $\tau_h(\mathbf{a},o) \leq 1$ for immigrant groups captures the extent to which immigrants differ from natives in their effective skill. For example, imperfect transferability of a worker's skills across countries or lower-quality foreign institutions that lead to less human capital accumulation on average will be reflected in $\tau_h(\mathbf{a},o)$. The joint match value of a worker of type $(x,\mathbf{a},o)$ employed in a firm of type p is then

$$rV(p,x,\mathbf{a},o) = \max_{s,\{\eta_k\}_{k\in\mathcal{K}}\geq 0}\Big\{f(p,h(x,\mathbf{a},o)) - c_S(s;\mathbf{a},o) + \zeta_1(s)\beta(\mathbf{a},o)\int_{p}^{1}[V(q,x,\mathbf{a},o) - V(p,x,\mathbf{a},o)]\tau_{S1}(q,\mathbf{a},o)\hat{\lambda}(q,\mathbf{a},o)dq + \delta(\mathbf{a},o)[W_0(x,\mathbf{a},o) - V(p,x,\mathbf{a},o)] + \delta_r(\mathbf{a},o)\beta(\mathbf{a},o)\int_{\mathcal{R}(x,\mathbf{a},o)}^{1}[V(q,x,\mathbf{a},o) - V(p,x,\mathbf{a},o)]\tau_{S1}(q,\mathbf{a},o)\hat{\lambda}(q,\mathbf{a},o)dq + \sum_{k=1}^{K}\eta_k[V(p,x,\mathbf{a}+\iota_k,o) - V(p,x,\mathbf{a},o)] - \sum_{k\in\mathcal{K}}c_{\eta_k}(\eta_k)\Big\}, \tag{7}$$

where the first line provides the flow output of the match net of workers' on-the-job search costs.

[23] Match production does not depend on the other matches within the firm, which implicitly assumes workers enter production linearly separable from one another. This is a standard assumption in the search literature and is necessary for tractability. While some evidence suggests immigrants and natives are complements in production, this complementarity is usually defined within broad geographic, education, and/or occupational groups (e.g., Piyapromdee (2021)). It is less clear that immigrants and natives are compliments in production at the firm level, and existing evidence suggests firms view workers as substitutes conditional on ability (Chan *et al.* (2024)).

Matches between a worker and a firm may end in three ways, which are reflected in lines 2-4 of equation 7. First, workers may voluntary quit when they obtain an offer at a firm with higher match value. The additional value generated from this on-the-job search is given in the second line, where employed workers who obtain a new job offer with a firm of type q accept the job and voluntarily move when $q \geq p$. As in Bagger and Lentz (2019) I assume for tractability that employed workers choose on-the-job search effort to maximize joint match value. Secondly, workers receive exogenous layoff shocks at rate $\delta(\mathbf{a}, o)$, in which case they move into unemployment (third line). Finally, workers also receive exogenous reallocation shocks at rate $\delta_r(\mathbf{a}, o)$ in which case they draw a new job offer prior to separation, as in Jolivet *et al.* (2006) (fourth line). Both types of shocks δ and δ_r will be necessary to capture worker mobility patterns from employment to unemployment and from higher rank firms to lower rank firms.

3.5 Immigrant Assimilation

The final line in equations 6 and 7 demonstrate how immigrant assimilation impacts workers' decisions and value functions. In both unemployment and unemployment, for each dimension k such that $a_k = 0$, an immigrant worker receives an assimilation shock at rate η_k that transfers them to the native space ($a_k = 1$). The assimilation rate η_k may be either an exogenous parameter or an endogenous choice by the worker. In particular, immigrants will choose assimilation effort η_k subject to convex cost $c_{\eta_k}(\eta_k)$ for each $k \in \mathcal{K}$, where $\mathcal{K} \subseteq \{1, \ldots, K\}$ denotes the set of endogenous assimilation decisions. This shock changes the worker's assimilation state from $\mathbf{a}$ to $\mathbf{a} + \iota_k$, ι_k being the k^{th} unit vector, which in turns impacts the worker's flow value and/or future job prospects, thus shifting their value function.

To fix ideas, I will allow new immigrants to differ from natives in four dimensions: (i) worker productivity ($k = 1$), (ii) their network of personal contacts ($k = 2$), (iii) search barriers that make job finding more challenging ($k = 3$), (iv) parameters impacting endogenous and exogenous job mobility ($k = 4$). Consider first assimilation in worker productivity: suppose immigrants arrive lacking destination-specific skills, making them less productive than native workers ($\tau_h(\mathbf{a}, o) < 1$ when $a_1 = 0$). After arrival, immigrants may then invest in destination-specific skills at cost $c_{\eta_1}(\eta_1)$—e.g., representing their cost of time—such that at rate η_1 they acquire the necessary skills ($a_1 \to 1$ and $\tau_h(\mathbf{a}, o) \to 1$) and become as productive as a native of the same ability type x.

Assimilating along the network and search dimensions function similarly: immigrants arrive with with a distinct network of personal contacts ($\mathcal{N}(\mathbf{a}, o) \neq \mathcal{N}(\mathbf{1}, 0)$ when $a_2 = 0$) and may face a search barrier ($\tau_{Si}(p, \mathbf{a}, o) < 1$ when $a_3 = 0$), both of which impact the rate and distribution of job opportunities. Immigrants may then incur some cost $c_{\eta_k}(\eta_k)$ for $k = 2, 3$—e.g., the effort of networking or the substantial time and expenses associated with foreign credential recognition—such

that at rate η_k immigrants receive an assimilation shock ($a_k \to 1$). For $k = 2$, this shock transfers immigrants from their co-national referral network to the native network ($\mathcal{N}(\mathbf{a}, o) \to \mathcal{N}(\mathbf{1}, 0)$), improving their access to job information. For $k = 3$, the assimilation shock removes the search barrier $\tau_{Si}(p, \mathbf{a}, o) \to 1$), allowing immigrants to obtain the same effective search technology as natives. The final dimension, job turnover involves the removal of differences between immigrants and natives in terms of exogenous separation rates and search costs ($\delta(\mathbf{a}, o), \delta_r(\mathbf{a}, o), c_S(s; \mathbf{a}, o)$), which collectively account for the job mobility patterns among new immigrants (section 2.3.1). I model this final channel as exogenous since the microfoundations of these immigrant-native differentials—e.g., firms' firing policies—are more appropriately thought of as a process immigrants take as given. [24]

The model set-up imposes that immigrant-native wage inequality will arise from three main sources: (i) lower match productivity due to lacking destination-specific skills, (ii) poorer employment allocation due to a combination of lower skills and allocative barriers, and (iii) a lower outside option that makes immigrants more willing to accept lower wages. The first two sources are both fundamentally about immigrants producing less than natives, either because they are individually less productive or because they are sorted into lower productivity firms. The third source is about immigrants' ability to command higher wages conditional on match productivity. In equilibrium, allocative barriers impact immigrants' job prospects which lowers their value of unemployment and the rate of receiving outside offers such that immigrants will tend to accept lower wages than than an equally productive native in the same firm.

The model permits other sources for why immigrants would accept lower wages. For example, Dustmann *et al.* (2024) argue that, if immigrants consume some of their income in their home country where prices are lower, then the effective real wage is higher in the destination country. If the real wage in the home country plays a role in determining the immigrants' outside option, this can result in immigrants accepting lower wages than natives. The model would capture this explanation by assigning immigrants a lower flow value of unemployment $b(x, \mathbf{a}, o)$, which in turn directly shifts entry wages from unemployment. In practice, I find the model replicates the (untargeted) immigrant-native entry wage gap without requiring this additional dimension of inequality. This is unsurprising given the empirical context of this paper. Permanent Residents (PRs) in Canada, who make up 90% of immigrants, are granted indefinite stay and the same labor market rights as natives, including access to employment insurance. Therefore, once admitted to Canada it is reasonable to assume their outside option depends on the economic conditions in Canada rather than their home country. In the estimation, I will therefore assume all worker groups have the same bargaining power ($\beta(\mathbf{a}, o) = \beta$) and unemployment flow value conditional on effective

[24] Bowlus *et al.* (2016) employs a similar stochastic process of immigrant assimilation, but there the assimilation shock is exogenous, one-dimensional, and does not depend on the worker's state.

worker productivity ($b(x, \mathbf{a}, o) = f(0, h(x, \mathbf{a}, o))$).

The fact that assimilation is endogenous has intuitive implications. For example, production complementarities in match output f will make the return to skill investment larger at higher productivity firms, and therefore workers will invest more intensively when employed at higher productivity firms relative to lower productivity firms or unemployment. The worker's realized skill accumulation is therefore history-dependent: destination-specific skills will be gained more quickly in higher productivity jobs.[25] Conversely, the unemployed or those lower on the job ladder have higher returns from networking or improving their search efficiency, leading to lower investment in these channels as workers climb the firm ladder.

3.6 Immigrant-native sorting differentials in equilibrium

In equilibrium, the rate at which workers' find new job through referrals is determined by flow equations that equate the mass of referrals being distributed and received. Using these conditions, I show in Appendix B.2 that the total rate of finding a type p job per unit of efficient search is,

$$\hat{\lambda}(p, \mathbf{a}, o) = \hat{\lambda}^F(p) \underbrace{\left(1 + \phi\bar{\sigma}(p, \mathcal{N}(\mathbf{a}, o)) \frac{N^s}{N^s(p, \mathcal{N}(\mathbf{a}, o))}\right)}_{\text{Referral multiplier}}, \tag{8}$$

where with a slight abuse of notation I have defined $N^s(p, \mathcal{N}) \equiv \sum_{(\mathbf{a},o)\in\mathcal{N}} N^s(p, \mathbf{a}, o)$ as the total effective search mass toward type p firms among workers belonging to network $\mathcal{N}$.

Equation (8) states that that the total job finding rate per unit of effective search is equal to the formal job finding rate times a subgroup-specific multiplier terms that arise due to the presence of segmented referral networks. The referral multiplier depends on firms' internal recruiting intensity (ϕ), the proportion of workers employed by type p firms that belong to the same network ($\bar{\sigma}(p, \mathcal{N}(\mathbf{a}, o))$), and the search competition created by other workers in the network ($N^s(p, \mathcal{N})/N^s$).

This equilibrium job finding function is the key for understanding how networks contribute to immigrant-native inequality. If there are no referrals ($\phi = 0$) or if each worker is connected to a homogeneous network (no ethnic homophily) then all workers face the same job arrival function per unit of effective search, as in standard search models. However, when $\phi > 0$, the rate and the distribution of job opportunities that a worker has access to now depends explicitly on the employment distribution of their personal contacts. If immigrants face labor market barriers—such as imperfect transferability of skills, search barriers, or higher job instability—they will, in equilibrium, be

[25] Adda *et al.* (2022) also have history-dependent human capital investment profiles. There, human capital investment varies due to preference shocks that affect the probability of return-migration. Here, human capital investment varies depending on the worker's realized labor market state.

employed at lower rank firms than native workers. Since the distribution of job offers obtained through referrals depends on the employment distribution of the network, the segmentation of referral networks can amplify differences in the types of jobs immigrants have access to. While other work has modeled job finding through referrals (see Dustmann *et al.* (2016), Arbex *et al.* (2019), Galenianos (2021), and Moon (2023), among others), no other work I am aware of embeds referrals into an equilibrium model with sorting to highlight their implications for between-group inequality.

4 Model Identification and Estimation

In this section, I discuss identification and estimation of the model parameters and present the fit of the estimated model to the data. I solve and simulate data from the model at a monthly time frequency and then estimate parameters by indirect inference, matching moments and coefficients from auxiliary regressions on simulated data from the model to their empirical counterparts. I target moments related to workers' wages and mobility patterns, with a key emphasis on the gaps between immigrant and native workers. I leave moments related to immigrant assimilation in firm productivity measures untargeted and use these as validation that the model accurately captures the mechanisms leading immigrants to settle into lower productivity firms.

4.1 Parameterization and Normalizations

I approximate the continuous heterogeneity in worker and firm productivity types using discrete grids $x_1, \ldots, x_{20}$ on $[0, 1]$, and $p_1, \ldots, p_{20}$ on $[0, 1]$. The model therefore has $20 \times 2^K = 320$ different worker types for each immigrant group o, allowing for rich heterogeneity among immigrants. I will focus on the case with two origin groups—immigrants and natives ($o \in \{0, 1\}$)—which offers a natural benchmark and reduces computational cost. In section 5.3 I further break up immigrants by channel of entry (economic, family, or refugee) to allow for more targeted policy analysis.

4.2 Identification

4.2.1 Network parameters

Segmented referral networks imply that workers obtain job information through other co-national workers, and therefore networks will manifest in the administrative data in the form of co-national hiring patterns. While referral networks are not the only mechanism through which such hiring patterns can arise, I argued in Section 2.3.3 that the observed patterns are inconsistent with immigrants selecting into high co-national firms for other reasons, such as preferences or productivity.

I therefore use the co-national sorting patterns to identify the referral intensity parameter ϕ. As validation, I find that this leads to referral usage that is consistent with survey data.

From the firms' problem in equation 5, one can show that, conditional on firm j hiring a new worker out of unemployment (UE transition) at time t, the probability that this hire belongs to origin group o is approximately[26]

$$P[o|j, UE, t] \approx \frac{P[o|p_j, UE, t, Formal]}{1+\phi} + \frac{\phi}{1+\phi}\tilde{\sigma}_{j,o,t}$$

where $P[o|p_j, UE, Formal]$ is the probability that a new hire found through the formal channel is from origin o, p_j is the productivity type of firm j, and $\tilde{\sigma}_j(o)$ the share of workers at j from origin group o. Letting $s_{j,o,t}^{Hires,UE}$ denote the share of workers from country o hired out of unemployment by firm j at time t, this leads to the regression

$$s_{j,O(i),t}^{Hires,UE} = X_{j,O(i),t}\boldsymbol{\beta} + \frac{\phi}{1+\phi}s_{j,O(i),t}^{Inc} + \epsilon_{ijt} \tag{9}$$

where $X_{j,O(i),t}$ includes country of origin and firm productivity fixed effects. In practice I include fixed effects for city-year, country-year, industry, and percentiles for firms' poach rank, mean wage, and employment size. Letting $\gamma \equiv \frac{\phi}{1+\phi}$ I find that $\hat{\gamma} = 0.47$ implying $\hat{\phi} = 0.89$. In the model, $\frac{\phi}{1+\phi}$ is also the share of workers hired through referrals, which assigns intuitive economic meaning to the co-national sorting coefficients and implies that 47% of workers are hired through referrals, perfectly in line with the survey evidence (Topa (2011)).

4.2.2 Search and transition technology

Job turnover: The search cost function takes the form $C_S(s; \mathbf{a}, o|a_4 = 1) = c_{S0}s^{1+1/c_{S1}}/(1 + 1/c_{S1})$ for natives and assimilated immigrants, and $C_S(s; \mathbf{a}, o|a_4 = 0) = \tau_{C_{S0}}C_S(s; \mathbf{1}, o)$ for unassimilated immigrants. The search cost shifter $\tau_{C_{S0}}$ captures differences in new immigrant search behavior arising, for example, from differences in cost of time. Similarly, $\delta(\mathbf{a}, o|a_4 = 1) = \delta$ and $\delta_r(\mathbf{a}, o|a_4 = 1) = \delta_r$ for natives and assimilated immigrants; $\delta(\mathbf{a}, o|a_4 = 0) = \tau_\delta\delta$ and $\delta_r(\mathbf{a}, o) = \tau_{\delta_r}\delta_r$ for unassimilated immigrants. The parameters τ_{δ_r} and τ_δ dictate the relative rate of exogenous separation shocks.

I add to the set of empirical targets the native EE transition rate from firms in the first and fourth poach rank quartile, both in total and conditional on the worker's job tenure being greater or equal to 24 months, and further add the corresponding gaps for new immigrants with 5 or less years in Canada. The EE rates at the bottom of the firm rank distribution will determine the search

[26]The expression holds with equality when there is no assimilation in a worker's network, so that a worker's origin group o is sufficient to define their network $\mathcal{N}$. In the data, assimilation along this dimension is very slow.

cost shifter parameters c_{S0} and $\tau_{C_{S0}}$, as these concern the rate of voluntary EE transitions. Since the large number of transitions out of higher rank firms will not easily be explained by voluntary on-the-job search, the EE rates out of firms at the top of the rank distribution will determine the reallocation shock parameters δ_r and τ_{δ_r}. The high EE mobility for new immigrants will therefore be explained by a combination of new immigrants (i) starting out in the labor market lower on the firm ladder, which naturally leaves more scope to move to better jobs, (ii) exerting higher search effort leading to more voluntary transitions, and (iii) being subject to more frequent involuntary job reallocations.

Since the rate of match destruction shocks (δ, τ_δ) and the corresponding rate of immigrant assimilation (η_4) are exogenous to workers, I conserve on internally estimated parameters by setting $\delta = 0.011$, $\tau_\delta = 2.75$, and $\eta_I = 0.025$ outside the estimation routine, finding that this yields a tight fit to the native EU rate and EU assimilation profile for immigrants.

Returns to search: Following Bagger and Lentz (2019), I use linear search intensity functions $\zeta_0(s) = \mu_0 + \kappa_0 s$ and $\zeta_1(s) = s$. I parameterize $\tau_{Si}(p, \mathbf{a}, o|a_3 = 0) = e^{-\tau_{S1i}p}$, $i \in \{0, 1\}$ for unassimilated immigrants, which governs immigrant-specific search barriers off- and on-the-job. This functional form assumes barriers to job finding are small for lower productivity jobs than higher productivity ones, which is consistent with job finding rate gaps across the firm distribution. Immigrants then overcome search barriers at rate η_3 at cost $C_{\eta_3}(\eta_3) = c_{\eta_3 0}\eta_3^{1+1/c_{\eta 1}}/(1 + 1/c_{\eta 1})$, which captures, for example, the substantial time and expenses associated with foreign credential recognition. The return to search intensity for unemployed native workers (κ_0) will be determined by the mean native unemployment duration, which in the data is 7.3 months. I then add the first 10 years of the immigrant assimilation profile in unemployment duration identify immigrant barriers to unemployed job search (τ_{S10}) and the assimilation cost shifter $c_{\eta 3 0}$. Without more detailed information on immigrant search behavior, I am not able to separately identify differences in cost of search $(\tau_{C_{S0}})$ from on-the-job search barriers (τ_{S1}). I therefore set $\tau_{S1} = 0$, so that immigrants in the model face no barriers to job search once employed. I therefore view the quantitative effects of search barriers in the following section as a lower bound. Finally, I set $\mu_0 = \delta_r$ following Bagger and Lentz (2019) and $C_{S1} = 3.6$ following Faberman *et al.* (2022).

Vacancy posting: Firms post vacancies at convex cost $C_V(v) = c_{V0}v^{1+1/c_{V1}}/(1 + 1/c_{V1})$. Since the vacancy cost elasticity has a direct effect on the firm size distribution, I identify this parameter using the 90-10 percentile ratio in firm employment size. Empirically, I find this ratio to be 29.0. Following Bagger and Lentz (2019) and Faberman *et al.* (2022), I normalize the vacancy cost shifter c_{V0} such that market tightness is equal to one. In each counterfactual scenario, I allow labor market tightness θ to adjust.

4.2.3 *Productivity distributions and the production function*

I let worker and firm productivity types be distributed according to a Rayleigh distribution, akin to a one-parameter log-normal, with scale parameters α_x and α_p. I further assume that immigrants and natives draw their fundamental productivity types x from the same distribution.[27] Then, a match between a firm of productivity p and a worker with effective human capital h generates 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 worker human capital in production and f_1 governs production complementarities. Finally, I allow for classical measurement error in monthly wages ϵ_w, where $\epsilon_w \sim N(0, \sigma_w)$.

I exploit the matched employer-employee structure of the data to identify the worker and firm productivity distributions and the production function. In particular, I include a two-way fixed effect equation to my set of auxiliary models

$$w_{ijt} = \psi_{\pi_p(j)} + a_i + r_{ijt} \tag{10}$$

where w_{ijt} is log monthly wages for worker i at firm j at time t, $\psi_{\pi_p(j)}$ are firm fixed effects where firms are clustered by poach rank percentile $\pi_p(j)$, a_i is an individual fixed effect and r_{ijt} is an error term. I include the standard deviation of the estimated firm and worker effects (sd$(\hat{\psi})$ and sd$(\hat{a})$), the correlation between them (corr$(\hat{\psi}, \hat{a})$), and the standard deviation of wages (sd(w)) and the residual (sd$(\hat{r})$) in the set of moments. Dispersion in the worker and firm effects pins down the distributional parameters α_x and α_p, and dispersion in the residual determines the extent of measurement error, governed by σ_w. In the production function, I set $f_0 = 2/3$ following estimates in Lise *et al.* (2016) and Bagger and Lentz (2019), and identify the complementarity parameter f_1 from the correlation between worker and firm effects.[28] I find that sd$(w) = 0.87$, sd$(\hat{\psi}) = 0.13$,

[27] The distribution of immigrant worker productivity relative to natives would be identified by permanent differences in wages that remain after all immigrant workers have assimilated. Although we never observe this figure, our assimilation estimates from Figure (1) suggest that, given enough time, wages converge. I therefore make the simplifying assumption that the distribution of *potential* human capital—i.e., the distribution immigrants converge to as they dispense with barriers to applying their human capital—is the same. Another way of putting this is that in a counterfactual world where the stock of immigrants were born into the host country, under host country institutions, language, culture, etc., they would have the same distribution of ability.

[28] As Bagger and Lentz (2019) document, the correlation between worker productivity and their wage fixed effect can be weak when $f_1 < 1$. This is due to the dynamic nature of expected future wages: High-skill workers are willing to take temporary wage reductions in anticipation of larger future wage gains, implying they can have lower wages than less-skilled workers in the same firms. Despite this, the correlation is typically positive (and more so when β is not too small, as in my case). Moreover, by first clustering firms into poach rank deciles rather than using individual firm identifiers in the two-way fixed effects specification, I avoid the well-documented "limited mobility bias" problem associated with the standard Abowd *et al.* (1999) regression which serves to downward bias the correlation between worker and firm types. See Bonhomme *et al.* (2022) for a discussion of this issue and a comparison of alternative

$\text{sd}(\hat{a}) = 0.66$, $\text{sd}(\hat{r}) = 0.53$ and $\text{corr}(\hat{\psi}, \hat{a}) = 0.15$ in the data.

Immigrants land with a human capital wedge τ_h such that they are effectively less productive than native workers, and then overcome this wedge by investing in host-country specific skills at cost $C_{\eta_H}(\eta_H) = c_{\eta_H 0}\eta_H^{1+1/c_{\eta 1}}/(1 + 1/c_{\eta 1})$. I therefore add the entire wage assimilation profile to the set of targets. If the initial wage gap cannot be explained by other differences between immigrants and natives, this requires a lower human capital among new immigrants to generate the lower observed wages. The rate at which wages converge then determines the cost shifter $c_{\eta_H 0}$, and the curvature of the profile identifies $c_{\eta 1}$.

4.2.4 Remaining exogenous parameters

I set the bargaining parameter to $\beta = 0.5$, discounting to $\rho = 0.004$, equivalent to an annual discount rate of 5%, and the labor market exit rate to $d = 0.0041$, implying a mean labor force duration of 20 years. The formal meeting function is Cobb-Douglas with elasticity equal to 0.5, following Petrongolo and Pissarides (2001). The mass of firms is set to $N^f = 0.065$ to match the ratio of firms to worker population in the data.

4.3 Estimation procedure

I estimate the model parameters by indirect inference, which involves finding the parameter vector $\boldsymbol{\omega}$ that minimizes the weighted sum of squared percent deviations between the empirical moments and moments calculated using simulated data from the model (see Gourieroux *et al.* (1993)). In total, there are 21 structural parameters to estimate using 48 empirical targets. To simulate the model for a given parameter vector $\boldsymbol{\omega}$, I first solve the fixed point problem for the value of unemployment W_0 and the match V, defined by equations (6) and (7). Given V and W_0, I obtain all other equilibrium objects, including the job arrival rate, the optimal search, assimilation, and recruiting decisions, the distribution over labor market states and wages, and the wage function.

Using this solution, I simulate labor market histories for a sample of 100,000 workers at a monthly time frequency. To replicate the structure of the Canadian administrative data, I simulate over 19 years to build employment histories, keep only the last 10 years, and then collapse the simulated data to the worker-firm-year level. Finally, let m_i, $i \in \{1, \ldots, 48\}$ be the i^{th} empirical moment and $\tilde{m}_i(\boldsymbol{\omega})$ the corresponding simulated moment, where $\tilde{m}_i(\boldsymbol{\omega})$ is calculated identically as in the empirical data. I minimize the sum of squared percent deviations between the empirical moment and the corresponding simulated moment, $d_i(\boldsymbol{\omega}) \equiv (\tilde{m}_i(\boldsymbol{\omega}) - m_i)/m_i$, by solving

$$\hat{\boldsymbol{\omega}} = \arg\min_{\boldsymbol{\omega}} \mathbf{d}(\boldsymbol{\omega})' \mathbf{W} \mathbf{d}(\boldsymbol{\omega}) \tag{11}$$

strategies for estimating the true correlation between worker and firm types.

where $\mathbf{d}(\boldsymbol{\omega})$ is a stacked column vector of the moment conditions $d_i(\boldsymbol{\omega})$ and $\mathbf{W}$ is the weighting matrix. I define the weighting matrix following Guvenen *et al.* (2021) by grouping my empirical moments into four sets—(i) search and transition moments, (ii) ethnic sorting moments, (iii) wage gap moments, and (iv) second-order wage moments—and then assigning an equal weight of $1/4$ to each set and an equal weight for each moment inside a set.[29]

Finally, to solve for (11) I implement a version of the global optimization algorithm developed in Guvenen *et al.* (2021). This algorithm involves first calculating the objective function for a large number of random parameter vector draws, and then using a small subset of the best draws in a local search procedure. See Appendix C.2 for more details.

4.4 Model fit and validation

I present the internally estimated parameters in Table (3) and find that new immigrants differ from natives in a number of ways. First, immigrants have a lower cost of job search ($\tau_{c_{S0}} = 0.23 < 1$), which helps explain the high EE transition rates for new immigrants. Second, immigrants have higher job reallocation rates ($\tau_{\delta_r} = 1.59 > 1$) and match separation rates ($\tau_{\delta} = 2.75 > 1$, set exogenously), which explains the high EU transition rates for new immigrants and also helps explain the high EE rates out of high-rank firms.

Third, immigrants have lower returns to job search out of unemployment, which helps explain the high unemployment durations among new immigrants. The search barrier parameter estimate of $\tau_{s0} = 2.85 > 0$ implies that, on average, unemployed new immigrants obtain only 55% of the job offers that a native worker of the same ability and applying the same search effort would receive. This differential return to search effort is remarkably similar to Oreopoulos (2011)'s finding in the Canadian labor market that immigrant resumes receive about half the number of call-backs relative to otherwise similar native resumes. The model leaves open the underlying sources of this lower return to job search. For example, discrimination, lacking recognition of foreign credentials, and language barriers could all play a role.

Fourth, immigrants land with lower human capital than native workers. The estimated human capital wedge of $\tau_h = 0.39 > 0$ implies that a median-ability immigrant at the median-productivity firm is only about two-thirds as productive as a same ability type (same x) native worker. This human capital wedge captures both the imperfect transferability of pre-migration skills, as well as the possibility that net skill accumulation is lower on average in foreign countries due, for example, to lower quality education systems. That immigrants land with lower human capital is necessary

[29] For example, there are 10 moments related to labor market transitions that are used to identify the search and transition parameters, and therefore each of these will receive a weight of $1/(4\times10)$. Since the number of parameters inside a set is somewhat arbitrary, this approach is preferred to weighting all moments equally as it avoids artificially increasing the importance of certain sets of parameters by increasing the number of targets inside the set.

Table 3: Estimated Parameter Values.

Parameter	Symbol	Value	Primary Source/Target
Search and Transition Parameters			
Search cost shifter	$c_{S0}, \tau_{c_{S0}}$	1.48, 0.23	EE transition rates, low rank
Reallocation rate	$\delta_r, \tau_{\delta_r}$	0.002, 1.59	EE transition rates, high rank
Unemployment search technology	κ_0, τ_{s0}	0.26, 2.85	Unemployment durations
Search assimilaton cost function	$c_{\eta_S 0}, c_{\eta_S 1}$	3.79, 24.01	Unemployment duration, assmilation
Vacancy cost function elasticity	c_{V1}	0.55	Firm size distribution
Productivity and Assimilation Parameters			
Productivity type distributions	α_p, α_x	0.21, 0.21	Std. of worker and firm effects
Production complementarity	f_1	-4.11	Corr. of worker and firm effects
Std. of measurement error	σ_w	0.49	Std. of residual
HC wedge	τ_h	0.39	Initial wage gap
HC assimilation cost function	$c_{\eta_H 0}, c_{\eta 1}$	51.16, 2.89	Wage assimilation
Network Parameters			
Personal referral probability	ψ	0.13	Ethnic sorting, low rank
Business referral cost function	c_{B0}, c_{B1}	1.56, 0.70	Ethnic sorting, high rank
Business referral scale parameter	ξ	3.18	Ethnic sorting, within-rank
Net. assimilation cost function	$c_{\eta_N 0}$	3.58	Ethnic sorting, assimilation

Notes: Internally estimated parameters from global search algorithm.

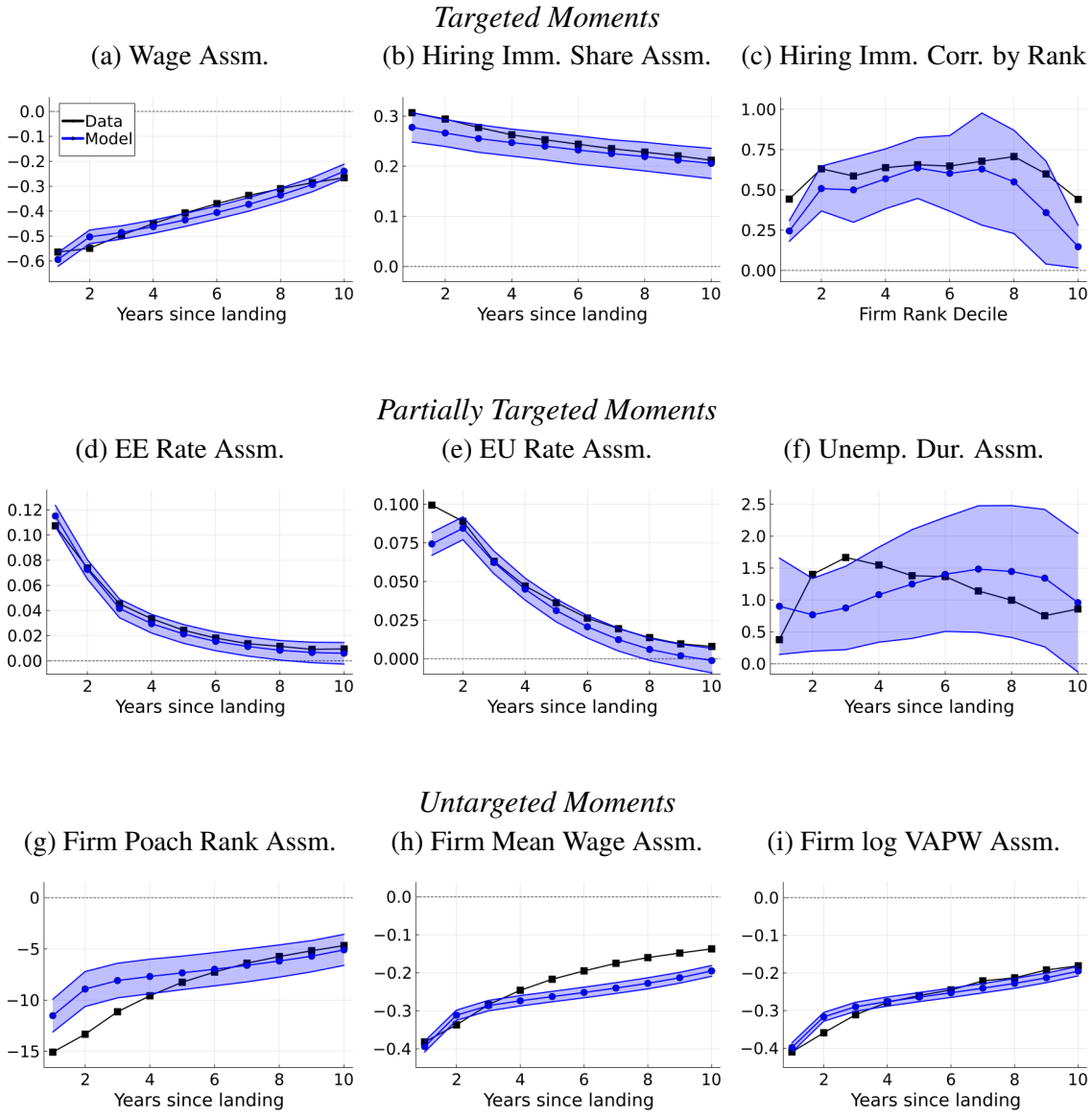
in the model to help explain the substantial gap in observed log wages, which cannot be explained solely by other differences such as job instability or search barriers.

Finally, I find a large role for ethnically segmented labor market networks, with 48% of all jobs in the economy being found through either a business or personal referral, consistent with survey evidence (see Topa (2011)). It is this feature of the model that generates the strong observed ethnic sorting patterns.

The estimated model does well at matching both the initial gaps in immigrant-native labor market outcomes and the dynamic subsequent assimilation process. In the first six panels of Figure (8), I plot the assimilation profiles for wages, the incumbent immigrant share among new hires, and EE, EU, and UE transition rates, comparing the model moments to their empirical counterparts. I also plot the rank-conditional ethnic sorting correlation across the rank distribution.

The bottom three panels of Figure (8) demonstrate the models ability to replicate immigrant-native differences in firm sorting by plotting assimilation profiles for firm poach rank, firm log mean wage, and firm log value-added per worker (VAPW). I find that, while the simulated moments tend to produce a slightly flatter assimilation profile than their empirical counterparts, overall the model approximates the initial gaps and assimilation patterns in firm sorting quite well. Importantly, these moments are untargeted in the estimation, implying the mechanisms of the model and the estimated differences between immigrant and natives naturally produce the observed firm

Figure 8: Model fit - Part A



Note: Figure plots the fit of the estimated model to the data. Blue line with circle markers and accompanying band report the mean and +/- 1.96 standard deviations from 1,000 independent simulations of the estimated model, where each simulation includes employment histories for 100,000 workers. 'Partially targeted' refers to figures where only a subset of coefficients were included in the objective function.

sorting patterns.

Finally, I present the fit of the remaining targeted moments in Table (4), including native transition statistics and second-order wage moments from the auxiliary wage fixed effect regression, again finding that these moments align closely with their empirical counterparts.

Table 4: Model fit – Part B

Moment	Model	Data	Moment	Model	Data
Other Transition Moments			*Other Ethnic Sorting Moments*		
Annual EE Rate, Nat. Rank Q1	0.13	0.17	Ethnic Hiring Corr., Imm.	0.71	0.81
Annual EE Rate, Nat. Rank Q4	0.08	0.12	Ethnic Hiring Corr., Imm. Within-rank	0.64	0.71
Annual EE-24m Rate, Nat. Rank Q1	0.06	0.08	*Auxiliary Wage Model and Firm Size Moments*		
Annual EE-24m Rate, Nat. Rank Q4	0.06	0.07	Std. of Wages	0.97	0.87
Mean Unemployment Duration, Nat.	8.11	7.31	Std. of Firm Rank Effects	0.14	0.13
Annual EE Rate Gap, New Imm. Rank Q1	0.05	0.07	Std. of Worker Effects	0.80	0.66
Annual EE Rate Gap, New Imm. Rank Q4	0.05	0.05	Std. of Residual	0.50	0.53
			Corr. of Worker and Firm Rank Effects	0.14	0.15
			90-10 Firm Size Ratio	22.50	29.00

Notes: Fit of simulated moments to empirical moments for all other moments targeted in the estimation. Simulated moments are from simulating employment histories for 100,000 workers from the baseline estimated model.

5 Quantitative Analysis

I now use the model to structurally decompose immigrant assimilation patterns (Section 5.1), quantify the impact of immigrant integration barriers on the aggregate economy (Section 5.2), and evaluate the long-run and aggregate effects of feasible immigrant integration programs (Section 5.3).

5.1 Immigrant Assimilation Decomposition

To structurally decompose the sources of immigrant inequality and assimilation, I sequentially remove differences between immigrant and native labor market parameters. I first remove network differentials by eliminating the segregation of personal contacts by ethnicity, and then eliminate differences in (ii) search barriers $\tau_{S0} = 0$, (iii) match destruction and reallocation rates $\tau_{\delta} = \tau_{\delta_r} = 1$, and finally (iv) initial human capital $\tau_h(\mathbf{a}, o) = 0$, such that new immigrants land with the same effective productivity distribution as native workers. The only remaining difference between worker groups is that immigrants land with a lower cost of job search effort $\tau_{C_S} < 1$. Since the order of the decomposition may matter, I also repeat this exercise in reverse order by first removing human capital differences and lastly removing network segmentation.

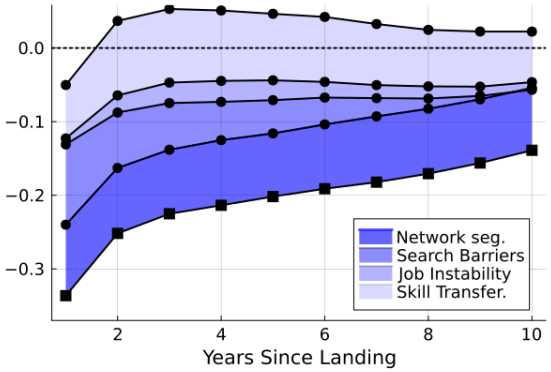
5.1.1 Assimilation in log productivity of employer.

I find that network segmentation accounts for about 30% of the baseline 33 log point gap in firm productivity (Figure 9a). Gaining access to the native network affords contacts in higher-productivity jobs, shifting upwards the distribution of job opportunities for immigrants. Search barriers have an equally large impact on initial immigrant sorting, accounting for another third the baseline gap. Removing search barriers impacts both the rate and distribution of job opportunities for unemployed immigrants, allowing immigrants to exit unemployment more quickly and start

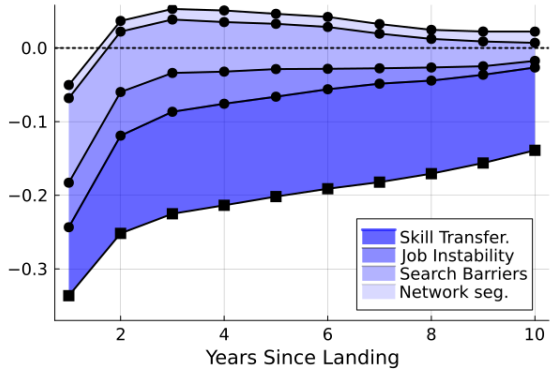
Figure 9: Structural Decomposition of Immigrant Firm Type Assimilation

Log Firm Productivity Assimilation

(a) Networks → Skills

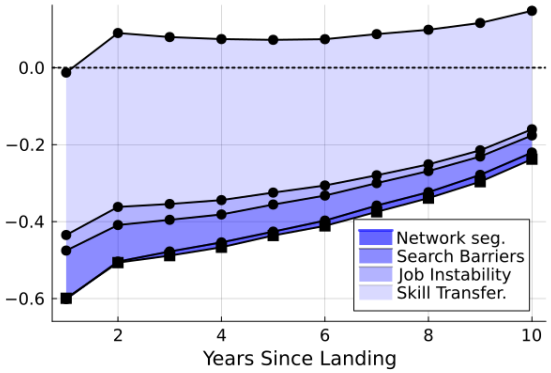


(b) Skill → Networks

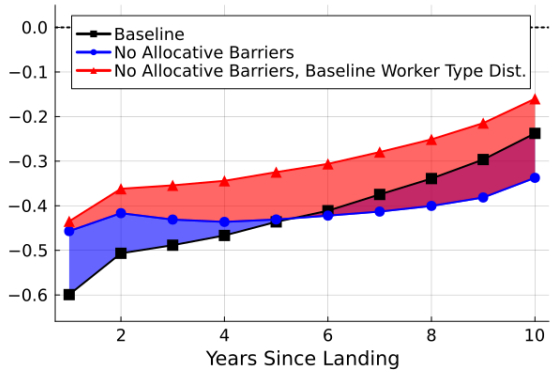


Log Monthly Earnings Assimilation

(c) Networks → Skills: holding employed worker ability distribution at baseline levels



(d) Allocative barriers: mean and within-worker wage changes



Note: Based on simulating employment histories for 100,000 workers. The square markers plot the assimilation profile from the baseline estimated model. The remaining lines sequentially remove differences between immigrants and natives and re-calculate the assimilation profile. (i) Network segmentation refers to eliminating the segmentation of referral contacts. (ii) Search barriers implies immigrants and natives now have the same effective job search technology. (iii) Job instability refers to eliminating differences in exogenous mobility rates. (iv) Skill transferability refers to eliminating differences in effective worker productivity. Within-worker refers to holding the employment distribution of worker ability as in the baseline.

higher on the firm ladder. Job instability has a smaller effect on firm sorting, accounting for only about 1 log point. Collectively, these allocative barriers account for about two-thirds of the baseline sorting gap.

Eliminating the immigrant productivity wedge closes the sorting gap by another 7 log points. This reallocation occurs because higher ability workers endogenously sort into higher productivity firms through higher search effort; a natural feature of search models with endogenous search effort

and a super-modular production function (see Bagger and Lentz (2019)). A small initial sorting gap of 5 log points remains because new immigrants start lower on the firm ladder compared to the average native who has already had time in the labor market.

Figure (9a) also demonstrates how the relative importance of each dimension of assimilation evolves over time. Search barriers, though acute at first, are overcome with time such that they have almost no impact 10 years after arrival. On the other hand, network segmentation and human capital differences are highly persistent, each accounting for about half of sorting gap 10 years after arrival.

Decomposing the gap in log firm productivity in the opposite direction, by removing human capital differences first and network segmentation last, yields similar results with one notable exception; removing network segmentation has almost no effect (Figure 9b). This decomposition highlights that network segmentation only serves to *amplify* the effects of other barriers—once other differences are removed, immigrant and native networks are nearly identical, and so further eliminating network segregation has minimal impact.

5.1.2 Assimilation in log monthly earnings.

Lastly, I quantify the effects of integration barriers on immigrant wages (Figure 9d). The difference between the square and circle markers reports the difference in mean wages between the baseline economy and the counterfactual where all allocative barriers are removed. At first, the removal of these barriers induces a positive wage effect, closing the initial wage gap by about one-quarter. However, this effect quickly closes and by year 6 reverses sign. The difference in means confounds increases in individual wages with an employment response that changes the ability distribution of employed immigrant labor. High-skill immigrants tend to realize similar wages, employment rates, and sorting across firms compared to native workers of the same ability type by searching and assimilating more intensively (see Figure D1). It is the lower-skill immigrants that struggle in the labor market the most, and therefore it is these workers who have the largest wage, employment, and firm sorting response when allocative barriers are removed (see Figure D2). The line with triangle markers controls for this composition effect by holding the employed immigrant distribution of ability at the baseline level, and recalculating the change in wages. The difference between this line and the baseline yields the average change in wages among workers who were employed in the baseline economy–akin to the average within-worker change in wages. Decomposing the within-worker wage gains shows that allocative barriers account for about one-quarter of wage inequality for both new and more established immigrants (Figure 9c).[30]

[30] Immigrants obtain slightly better sorting and wage outcomes in the final counterfactual relative to native workers because differences in search costs have not been removed.

Table 5: Aggregate Implications of Immigrant Barriers

	Total Output (%)		Output per Worker (%)		Wage (%)		Emp. Rate (p.p.)	
	Imm.	Tot.	Imm.	Nat.	Imm.	Nat.	Imm.	Nat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network Segmentation	0.9	-0.1	1.2	-0.3	1.2	-0.2	-0.1	-0.1
Search Barriers	6.1	0.8	0.5	-0.1	1.8	-0.2	5.4	0.6
Job Instability	2.5	0.3	1.3	-0.1	2.3	0.0	2.3	0.0
All Allocative Barriers	8.4	1.1	2.5	-0.3	4.6	-0.1	6.2	0.8
Skill Transferability	26.0	3.9	20.0	-0.1	20.9	-0.2	5.8	0.1
Skill + Allocative	32.1	4.7	21.1	-0.3	23.6	-0.3	9.9	0.7
All Differences	30.3	4.8	20.4	-0.2	19.7	0.2	9.2	1.0

Note: Change in aggregate outcomes relative to baseline economy. Changes in output per worker and wages hold the employment distribution of worker ability the same as in the baseline economy. (i) Network Segmentation refers to eliminating the ethnic segmentation of referral networks. (ii) Search Barriers refers to eliminating immigrants search wedge. (iii) Job Instability refers to eliminating differences in exogenous mobility rates. (iv) Skill Transferability refers to eliminating differences in effective worker human capital. All Allocative Barriers eliminates (i)-(iii). All Differences further eliminates differences in search costs.

5.2 Implications for Aggregate Productivity and Native Workers

Next, I consider the implications of immigrant-native inequality for for the aggregate economy (Table 5). In the first row, I eliminate the segmentation of referral networks. Removing segmentation has almost no effect on immigrant employment (column 7) but allows immigrants to reallocate into higher productivity firms (column 3), ultimately raising immigrant output and wages by about 1% (columns 1 and 5). This shows that the immigrant network delivers a job finding rate on par with natives, but a worse distribution of jobs. In contrast, eliminating search barriers and job instability (rows 2 and 3) improves immigrant output by 6.1% and 2.5%, primarily by increasing employment rather than improved allocation across firms. For example, eliminating search barriers increases the immigrant employment rate by more than 5pp (column 7) but only increases output per worker by 0.5% (column 3).

Eliminating all allocative barriers would increase immigrants' output (8.4%), employment (6.2pp), and wages (4.6%), and would raise total output by 1.1%. Eliminating differences in skills has a larger effect on immigrant output (26.0%) and immigrant wages (20.9%), but a smaller affect on immigrant employment (5.8pp).

Every counterfactual scenario has mild effects on native labor market outcomes (columns 4, 6 and 8). The result that one can improve the outcomes of immigrants without hurting natives arises from two offsetting forces—(i) removing integration barriers implies immigrants are now more effective in navigating the labor market, placing competition on natives, but (ii) firms endogenously respond to this new environment with more job creation, which natives benefit from. That these

forces offset each other is not mechanical but rather depends on the elasticity of firms' vacancy cost function.

5.3 Evaluating Immigrant Integration Policies

The previous analysis provides insights on how barriers to labor market integration affect immigrant outcomes, as well as the aggregate gains from removing such barriers and the mechanisms through which these gains arise. However, addressing barriers to immigrant integration is costly and eliminating all of them may not be feasible in practice. In this subsection, I use the model to evaluate the effects of two feasible and widely implemented immigrant integration programs—(i) formal language training programs (LTPs) and (ii) active labor market programs (ALMPs).

A number of empirical papers have used quasi-experimental methods to estimate the short-run causal effects of LTPs and ALMPs on immigrant labor market outcomes.[31] I use this literature to map the impact of these programs to the model parameters and then build on the literature by using my model to assess long-run and general equilibrium effects.

I set up a simulated randomized control trial (RCT) in which a small fraction ϵ of immigrants are treated by the integration program and therefore face less severe barriers. Since ϵ is small, this has a negligible effect on the aggregate economy or on the labor market outcomes of natives and untreated immigrants. Comparing treated to untreated immigrants over the first T years since landing, I find the change in immigrant labor market barriers necessary to induce the same wage and employment response identified in the literature. I set $\epsilon = 0.05$, so that less than 1% of the population is treated by the program and set $T = 5$ to be consistent with the estimates from the empirical literature. With the mapping between the program and model parameters in hand, I then simulate the long-run effects, isolate within-worker wage gains, and analyze implications for the aggregate economy, focusing on spillovers, output, and native workers.

5.3.1 Language Training Programs

Workers from linguistically distant source countries may arrive with poor or imperfect English that inhibits their ability to perform jobs tasks or secure employment. Almost 90% of Canada's PRs in 2015 had a mother tongue other than English or French and almost 25% report being unable to converse in either official language, suggesting language barriers may be severe for many immigrant workers.[32]

While language acquisition will happen naturally over time as immigrants work and live in the

[31] For studies on LTPs, see Sarvimäki and Hämäläinen (2016); Lochmann *et al.* (2019); Foged *et al.* (2024b); Foged *et al.* (2024a); for studies on ALMPs, see Battisti *et al.* (2019); Foged *et al.* (2022); Arendt (2022); Dahlberg *et al.* (2024); Foged *et al.* (2024a).

[32] Canada, IRCC (2017) Evaluation of the Settlement Program

host country, governments can expedite that process by offering formal LTPs. The details and the intensity of such programs will vary by context, but typically include around 200 hours of language training courses. The literature exploiting quasi-experimental methods across a range of policy reforms and host countries typically finds that such courses improve immigrant employment by about 2-5pp and increase mean earnings by about USD 1,100-3,000 (see Foged *et al.* (2024a)). Using this information I make two assumptions. First, I assume that such policies in the Canadian context would improve immigrant outcomes similarly, and target a 3.5pp increase in employment and a USD 2,000 (CAD 2,700) increase in annual earnings, which is approximately a 7% increase relative to the average new Canadian immigrant. Second, I assume that this policy works by a combination of improving worker productivity and improving their search efficiency. Specifically, I let the treatment be defined by two parameters $(x_H^{LTP}, x_S^{LTP}) \in [0,1]^2$, that proportionally reduce (i) the human capital wedge ($x_H^{LTP} \times \tau_H$) and cost of human capital assimilation ($C_{\eta H}(x_H^{LTP} \times \eta_H)$), and (ii) the search wedge ($x_S^{LTP} \times \tau_{s0}$) and cost of search assimilation ($C_{\eta S}(x_S^{LTP} \times \eta_S)$), for all treated immigrants. I find the parameters (x_H^{LTP}, x_S^{LTP}) such that treated immigrant employment rises by 3.5pp and wages by 7% relative to controls immigrants over the first 5 years after landing. This combination will be unique since skill and search barriers affect employment and wages differently; eliminating search barriers yields a strong employment response, but a weaker wage response, and vice versa for the skill wedge (see Table 5).

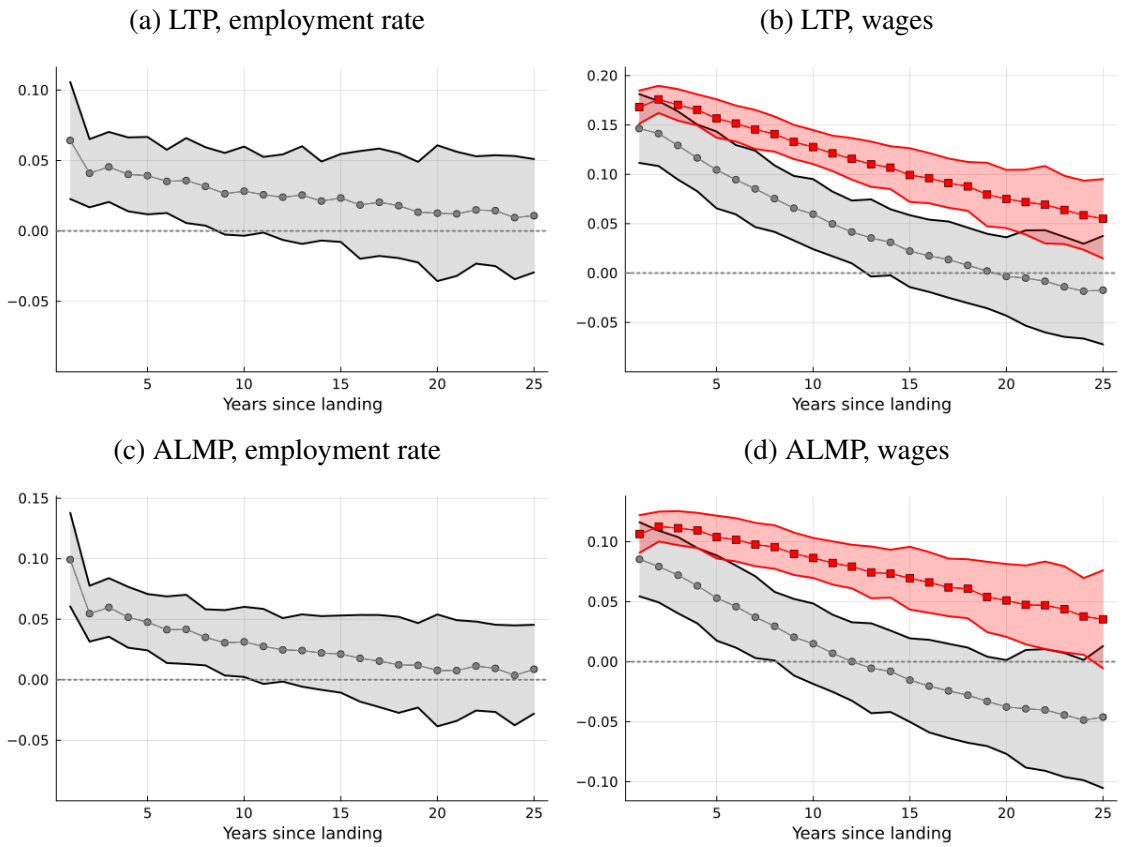
5.3.2 Active Labor Market Policies

ALMPs for immigrant integration usually involve a combination of training and job search assistance. Again, the details of these programs will vary by context, but studies establishing causal identification typically find that ALMPs raise the employment probability of immigrants by about 5pp and earnings by about USD 1,700 (see Foged *et al.* (2024a)), which is similar to the effects of ALMPs on unemployed native workers (see Ashenfelter and Card (1985) and Card *et al.* (2018)). I again assume that such programs would have similar effects on Canadian immigrants and target an employment effect of 5pp and an earnings effect of USD 1,000 (CAD 1,350), equivalent to a 3.5% increase in earnings for new immigrants. Since the core components of ALMPs are skill investments and search assistance, I again map this program to the model by finding the reduction in human capital and search barriers (x_H^{ALMP}, x_S^{ALMP}) necessary to raise new immigrant employment by 5pp and earnings by 6%.

5.3.3 Results of Policy Evaluation

I find that language training primarily affects immigrant human capital, with $(x_H^{LTP}, x_S^{LTP}) = (0.76, 0.90)$, whereas ALMPs are more balanced in helping immigrants find employment more

Figure 10: Dynamic policy effects based on simulated RCT



Note: Simulated impact of integration programs on treated immigrants relative to control. Gray lines report mean effect from the program; red lines report the effect holding the distribution of worker ability the same in the treated group as in the control group. Effects of programs have been mapped to model parameters by matching a simulated RCT to causal estimates in the literature, as described in the text. Language Training Programs (LTPs) reduce the extent and assimilation cost of human capital and search barriers to 76% and 90% of their baseline value, respectively. Active Labor Market Policies reduce the extent and assimilation cost of human capital and search barriers to 83% and 68% of their baseline value, respectively. Simulations are based on 100,000 immigrant workers, 5% of whom are treated by the program. Figures report the mean and +/- 1.96 standard deviation from 500 independent repetitions.

easily and making them more productive once employed, with $(x_H^{ALMP}, x_S^{ALMP}) = (0.83, 0.68)$. These results are consistent with the intention of each program, where language is typically viewed as a skill to be employed in the workplace whereas ALMPs typically offer matching assistance in addition to general skill investments.

Figure (10) plots the dynamic effects of LTPs and ALMPs on immigrant wages and employment rates. The effect of these programs on employment (panels a and c) is quite persistent, especially over the first 10 years, but slowly converges to zero as control immigrants assimilate. For wages (panels b and d), I plot both the mean change (gray) and within-worker change (red), where the latter holds the ability composition among the employed the same as in the control group. Focusing on within-worker wage changes, I find that both types of policies lead to highly persistent wage

Table 6: Aggregate Effects of Immigrant Integration Programs

	Total Output (%)		Output per Worker (%)		Wage (%)		Emp. Rate (p.p.)		Init. Skill Inv. (%)
	Imm.	Tot.	Imm.	Spill.	Imm.	Spill.	Imm.	Spill.	Imm.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LTP	8.9	1.3	6.3	0%	6.6	-3%	2.7	-13%	25%
ALMP	7.6	1.1	4.0	0%	4.4	-2%	3.3	-5%	25%

Note: Change in aggregate outcomes relative to baseline economy. Effects of programs have been mapped to model parameters by matching a simulated RCT to causal estimates in the literature. Language Training Programs refer to reducing the extent and assimilation cost of human capital and search barriers to 76% and 90% of their baseline value, respectively. Active Labor Market Policies refer to reducing the extent and assimilation cost of human capital and search barriers to 83% and 68% of their baseline value, respectively. Columns with (w) refer to within-worker changes, which denotes the change relative to baseline holding the employment distribution of worker ability the same as in the baseline economy.

increases; 25 years after the treatment, the wage effect remains at about one-third of its initial value. The differences between the mean wage change and the within-worker wage change highlight the importance of controlling for worker ability, especially when evaluating the long term effects.

Finally, in Table (6) I report the aggregate effects of scaling LTPs and ALMPs to the national level, such that all immigrants are treated by the program. I find that these programs substantially increase immigrant output (7.6-8.9%, column 1) and wages (4.4%-6.6%, column 3)), suggesting these policy interventions can each capture about one-quarter of the total available gains from eliminating all barriers to immigrant integration (Table 5). These output and wage gains are achieved through a combination of (i) directly increasing worker skills, (ii) reallocating immigrants to higher productivity firms, (iii) increasing immigrant employment rates (2.7-3.3pp, column 7), and (iv) increasing initial endogenous skill investments (by 25%, column 9).

Immigrants endogenously respond to the treatment by increasing skill investments partly because they find employment in higher productivity firms and partly because their job opportunities are better, both of which increase the returns to skill investments. This mechanism highlights that, by shifting immigrants' initial conditions, integration programs also lead to dynamic changes in immigrant behavior, partly accounting for the persistent effects of these programs.

The remaining columns highlight the spillover effects from increasing the scale of immigrant integration programs (columns 4, 6 and 8). Relative to when only a small fraction of immigrants are treated, the programs tend to have a slightly smaller treatment effect on wages (-2 to -3%) and employment (-5 to -13%). Improving immigrant outcomes will improve the employment distribution of the immigrant network, potentially leading to better access to jobs. However, it also creates additional competition for jobs. The negative spillover effects indicate that this competition channel dominates. Nevertheless, these spillover effects are small and programs are effective at improving immigrant performance.

6 Conclusion

The issue of how to effectively integrate immigrant workers to the host economy is a central policy challenge for receiving countries. This paper studies how barriers to labor market integration shape immigrant outcomes, the effect they have on the aggregate economy, and the capacity of host governments to mitigate these barriers through integration programs.

Using matched employer-employee tax file data from Canada linked with administrative immigrant landing records, I carefully document how immigrants differ from natives in the labor market, focusing on how immigrants allocate between firms and employment states. I uncover stark differences in sorting patterns between immigrants and natives that suggest immigrants face barriers to finding employment and climbing into higher paying jobs. I then build a general equilibrium labor market search model that exploits these sorting patterns to identify the key ways immigrants differ from natives beyond differences in worker ability. I estimate the model to the Canadian tax file data and find that immigrants experience higher job instability (e.g., last-in-first-out firing policies), barriers to job finding (e.g., discriminatory hiring practices), and segmented labor market networks. The gaps in sorting patterns dissipate with time in Canada as immigrants eventually overcome the barriers they face at arrival.

I then use the estimated model to conduct three sets of counterfactual exercises. I first decompose immigrant assimilation in wages and firm sorting, finding that a substantial share of immigrant-native inequality is due to barriers that distort the allocation of immigrant labor rather than differences in worker productivity. Second, I quantify the effects of these barriers on the aggregate economy. If government policy could eliminate allocative barriers, immigrant output would increase by 8.4% and total output by 1.1%. These gains are achieved without harming natives due to firms' endogenous job-creation response.

Finally, I evaluate two immigrant integration programs—language training programs (LTPs) and active labor market polices (ALMPs)—finding they lead to persistent improvements in wages, output, and employment. The gains from these policies are concentrated among low-skill immigrants and primarily arise from helping these immigrants exit unemployment, informing where policy efforts should focus. A more nuanced policy scheme that targets unemployed immigrants from certain subgroups, such as those arriving from linguistically distant source countries or arriving through non-economic channels, would likely target the population with the highest returns on investment.

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