MORE THAN JUST NEIGHBORS: IMMIGRANT NETWORKS AND JOBS IN HIGH-PAYING FIRMS

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ABSTRACT. We study whether neighborhood peers influence immigrants' access to high-paying employers. Using longitudinal employer–employee tax data linked to immigration records, we measure employer quality with firm-specific earnings premiums and exploit variation across neighborhoods within larger locales. We find that immigrant-peers raise employer quality, especially for job switchers, while native-peers have little effect. Peer effects are nearly twice as large when peers share a country of birth or mother tongue. Results are robust across specifications, underscoring identity-based neighborhood networks as a channel of immigrant labor market integration.

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1. Introduction

Employment in high-paying firms is central to immigrants' economic integration: shortfalls in immigrant employment at such firms account for a large share of the immigrant–native pay gap (Barth et al., 2012; Dostie et al., 2023; Hermansen et al., 2025). Major barriers to employment in these firms are search and information frictions, especially for immigrants who often face language barriers, have limited local knowledge, and possess few professional contacts (Borjas, 1995; Bertrand et al., 2000). Social networks can mitigate such barriers by transmitting vacancy information, facilitating referrals, and improving job–worker match quality (Granovetter, 1973; Montgomery, 1991; Topa and Zenou, 2015; Beaman, 2012).

Residential neighborhoods are pertinent in this context, because they provide a locus of social networks for immigrants whose labor market ties may be tenuous. Neighbors can share job leads, explain hiring practices, provide referrals, and offer job advice. Empirically, residential proximity predicts employment and employer allocation (Hellerstein et al., 2011, 2014; Schmutte, 2015), and referral-based search is an oft-emphasized channel through which peers transmit employer information and reduce screening frictions (Dustmann et al., 2016). Social similarity also matters since people tend to be more influenced by socially similar peers (McPherson et al., 2001), and cultural proximity can make employer signals more scrutable and credible (Dustmann et al., 2023b).

But do better-placed neighborhood peers actually help with immigrants' employment outcomes? Do they help them get or keep jobs in high-paying firms? If so, who exerts more peer influence: immigrant neighbors or native neighbors? And do peers who share a cultural background matter more? This paper sheds light on these issues by asking whether immigrants are more likely to work in high-paying firms when peers in their residential neighborhood do so; whether peer influence varies along the lines of shared immigrant, national, or linguistic identity; and whether peers effects are consistent with immigrants' employer mobility or job stability.

We find that peer effects matter for immigrants' employer quality: immigrants whose peers work for firms that pay higher premiums tend to work at higher pay-premium firms themselves, and these positive peer effects are consistent with an employer mobility margin rather than job stability. Peer effects are driven entirely by immigrant-peers; native-peers exert no effect. Among immigrant-peers, cultural commonality matters: effects are twice as large when they come from immigrants from the same (vs. different) country of birth, or speak the same (vs. different) mother tongue as the focal immigrant. Estimates are robust to a range of fixed effects and alternative specifications. We find that our design choice to exclude co-residing family members reduces the estimated impact relative to other studies—where family-member inclusion in neighborhood networks tends to inflate coefficients—underscoring that the relevant margin is extra-household neighborhood ties.

We use the Canadian Employer–Employee Dynamics Database (CEEDD)—a longitudinal linked employer–employee database covering the universe of Canadian tax filers—matched at the individual level to the Longitudinal Immigration Database (IMDB). These data report annual earnings, employers, two nested residential identifiers, and demographics (age, sex, education) alongside detailed immigration records (arrival cohort, country of birth, mother tongue). Our analysis focuses on a recent cohort of immigrants who lived in Toronto, Montréal, or Vancouver between 2001-2017, having arrived there within the five years prior. These three metropolitan areas are Canada's largest and most diverse, containing immigrant populations at the neighborhood level that are large enough to support disaggregated analysis.

Peer groups consist of residents of the same neighborhood excluding co-residing family members, so our focus is on extra-household exposure. Employer quality is measured by firm-specific earnings premiums from a two-way fixed-effects model of log earnings following Abowd et al. (1999) (AKM), estimated on the full CEEDD universe of immigrant and native workers. Peer networks comprise neighbors in the same postal code, distinguished by immigrant versus native status and, when relevant, by shared country of birth or mother tongue.

Our goal is to identify the effect of neighborhood peers' employer quality on immigrants' employer quality. Since immigrants are not randomly assigned to neighborhoods, two broad threats to identification are relevant. The first is correlated effects, arising from neighborhood sorting or common local shocks. We address this by exploiting plausibly exogenous assignment to neighborhoods within larger residential locales, taking advantage of the Canadian postal structure whereby smaller six-character postal codes ("neighborhoods") are nested within three-character codes ("locales"), designed for mail routing rather than socioeconomic demarcation. In our baseline, we condition on locale fixed effects, time fixed effects, and rich covariates; as a robustness check, we also include locale×year fixed effects. To support this identification strategy we show that, conditional on locale, there is little evidence of sorting on observables; we do not observe higher rates of cross-neighborhood relocation around job switches; and movers do not appear to sort into neighborhoods within a locale on the basis of future neighbors' job characteristics.

The second threat to identification is the reflection problem: peer effects may partly mirror contemporaneous peer characteristics rather than peer outcomes (Manski, 1993). This concern is mitigated here because firm-specific earnings premiums are estimated from complete work histories, which are predetermined (Schmutte, 2015; Cornelissen et al., 2017). Nonetheless, to avoid simultaneity we lag peer employer quality.

In the fully saturated specification—which conditions on locale fixed effects, individual covariates, peer composition, and prior employer quality—higher-quality neighborhood peers are associated with higher employer quality for immigrants. A one–standard-deviation increase in peer employer quality raises immigrants' own earnings by 2.3%. This estimate nearly triples when other household members are counted as belonging to the neighborhood network. Consistent with increased employer mobility, peer effects are concentrated among job switchers. By contrast, peers do not increase the probability of staying in a job—a finding that is inconsistent with more job stability. Positive peer effects are driven by immigrant-peers: when we split neighborhood networks into immigrants and natives, we find a positive immigrant-peer coefficient, and a near-zero native-peer coefficient.

Among immigrants, peer effects are stronger when identity is shared. Splitting immigrant-peers by country of birth and mother tongue, both same- and different-identity immigrant-peers matter, but coefficients are roughly twice as large for co-nationals and co-linguist neighbors. Native-peer effects on immigrants remain close to zero. Using natives as the focal group yields the mirror pattern: natives respond primarily to native-peers, with smaller effects from immigrant neighbors. Taken together, these asymmetries are hard to reconcile with undifferentiated neighborhood spillovers and are consistent with identity-based peer effects.

Heterogeneity analysis suggests that focal immigrants whose formal labor market ties are likely more tenuous tend to enjoy larger immigrant-peer effects, while those who seem better equipped for labor market integration ex-ante enjoy some native-peer effects. Specifically, immigrant-peer effects are larger for immigrants who are less educated, and among family and refugee admissions. By contrast, native-peer effects are more evident for older as well as more highly educated immigrants, and those from economic-class admissions. Again, these patterns are strongest among job switchers. While shared ethnic identity markers seem to matter, similarity along non-ethnic dimensions reveals a mixed picture. For men, only male immigrant neighbors yield positive coefficients whereas for women, immigrant- peers of both genders do. And immigrant-peer who—like our focal immigrants—are also relatively recent arrivals, exert a similar peer effect as those who have been in Canada for longer.

Our baseline results—a positive immigrant-peer and null native-peer effect—persist across a battery of checks. Estimates are stable when we impose more demanding fixed effects (including locale×year and country-of-birth×year); when we tighten minimum peer-count thresholds; when we drop very small population neighborhoods, and when we restrict our sample to immigrants who never changed neighborhoods. They are robust to alternative-peer network lag structures, and become more pronounced when we expand shared identity beyond national and linguistic delineations to world regions.

This paper contributes to three strands of literature: residential peer effects in labor markets, social networks and job search, and co-ethnic networks and immigrant labor market integration. First, we build on evidence that geographically proximate contacts shape employment and employer allocation. Early contributions document neighborhood spillovers in job finding and employment using variation in peer employment rates (Topa, 2001; Topa and Zenou, 2015; Bayer et al., 2008). Closest to our design is Schmutte (2015), who uses U.S. LEHD data and neighborhood composition to show that exposure to neighbors employed at higher-quality firms predicts subsequent employment at higher-paying employers. Our study builds on this, but from a different angle: our focus is firmly on immigrants; we distinguish immigrant- from native-peers; we are interested in shared identity; and we exclude co-residing family members to isolate extra-household neighborhood exposure.

Second, a foundational idea is that social ties transmit job information and facilitate matches (Granovetter, 1973; Montgomery, 1991). Empirical work documents referral and coworker effects on hiring, wages, and employer switching in linked administrative and experimental settings (e.g., Dustmann et al., 2016; Cornelissen et al., 2017; Glitz and Vejlin, 2021; Hensvik and Skans, 2016; Brouard et al., 2024; Hansch et al., 2024; Pallais and Sands, 2016; Beaman, 2012). We add to this literature by emphasizing the residential margin of network exposure rather than firm- or task-based links. While we do show that our results are consistent with employer mobility rather than job stability, we do not attempt to identify micro-mechanisms. Instead, we provide new evidence on how neighborhood exposure affects employment in higher-premium firms.

Third, a large literature studies how ethnic enclaves, co-ethnic density, neighborhood conditions, or refugee placement affect immigrant outcomes (e.g., Edin et al., 2003; Beaman, 2012; Damm, 2009, 2014; Martén et al., 2019; Stips and Kis-Katos, 2020). Much of this work relies on group shares or placement rules and examines employment rates or earnings levels. We extend this literature in three ways. First, rather than proxying for enclave quality or estimating the size effect of co-ethnic group, we focus on peer quality by using directly observed neighbor outcomes. Second, we focus on employer quality, not employment status or earnings. Third, we leverage comparatively granular measures of ethnic identity, building on recent work highlighting the role of shared identity in economic assimilation (Dustmann et al., 2023b; Caiumi and Simonsen, 2025), to show that peer effects are stronger when identity is shared by country of birth or mother tongue, and largely absent for native-peers of immigrants.

The paper proceeds as follows. Section 2 outlines our empirical framework and identification strategy. Section 3 describes the data, while Section 4 provides evidence in support of the identification strategy. Section 5 presents our main results. Section 6 explores mechanisms and heterogeneity. Section 7 reports robustness checks. Finally, Section 8 concludes.

2. Empirical Strategy

This section presents the empirical models used to estimate firm-specific earnings premium and neighborhood peer effects. It outlines the key challenges to the identification of peer effects, and describes how we address them.

2.1. **Firm-specific earnings premium.** We begin by estimating the outcome variable for the peer effects analysis—firm-specific earnings premiums—using a two-way fixed effects (AKM) model, following Dostie et al. (2023):

$$\ln y_{ijt} = \theta_i + \gamma' \boldsymbol{x}_{it} + \psi_{j(i,t)} + \tau_t + \eta_{ijt} \tag{1}$$

where y_{ijt} is annual real earnings of worker i from their main employer j in year t; θ_i is a worker fixed effect capturing time-invariant differences in earnings across workers; $\boldsymbol{x}_{it}$ is a vector of individual time-varying controls, which includes a normalized quadratic age term as well as marital status; $\psi_{j(i,t)}$ is the firm-specific earnings premium at firm j where i works in period t; τ_t is a year fixed effect; and η_{ijt} is an error term.

The AKM model in equation (1) can be conceptually grounded in a number of different theoretical models, including wage posting (e.g., Burdett and Mortensen, 1998), search and match (e.g., Mortensen, 2010), on-the-job search with wage bargaining (e.g., Cahuc et al., 2006), and monopsonistic wage setting (e.g., Card et al., 2018). We are agnostic about the precise theoretical mechanism at play, noting simply that there is a conceptual basis for the existence of a firm-specific earnings premium which can be retrieved by estimating the model.

2.2. **Linear social interactions model.** In our main analysis, we estimate a linear social interactions model to assess whether immigrants are more likely to work in high-paying firms when their residential neighbors do so. Our outcome of interest is the firm-specific earnings premium, $\psi_{it} \equiv \psi_{j(i,t)}$, estimated from model (1). Neighborhood networks are defined by co-residence in the same six-character postal code, excluding co-residing family members. For any variable z, we denote by $\overline{z}_{n(i),t-1}$ the exclusive mean among i's peers in their neighborhood $n(i)$ in year $t-1$. This convention applies both to the firm premium ($\overline{\psi}_{n(i),t-1}$) and to peer characteristics ($\overline{\boldsymbol{x}}_{n(i),t-1}$).

We use once-lagged values ($t-1$) in our main specifications, since meaningful social interactions are unlikely to be formed contemporaneously, especially in the case of residential movers; we show in Section 7 that our findings are robust to alternative lag structures, including twice-lagged and contemporaneous values. Additionally, this lag structure helps address concerns related to reverse causality by making the direction of the estimated peer effects—from established peer networks to current behavior—explicit. Pertinently, this rules out neighborhood, and by extension peer, selection coinciding with job switches.

2.2.1. *Preliminaries.* To set the stage, consider a linear social interactions model that captures peer effects for the full neighborhood network:

$$\psi_{it} = \alpha + \gamma' \boldsymbol{x}_{it} + \nu \psi_{i,t^-} + \phi\, \overline{\psi}_{n(i),t-1} + \delta'\, \overline{\boldsymbol{x}}_{n(i),t-1} + \lambda_{\ell(n(i)),t-1} + \tau_t + \varepsilon_{it} \tag{2}$$

where the outcome variable is the pay premium—estimated from the AKM model described in the previous section—of the firm in which individual i works at time t. The vector $\boldsymbol{x}_{it}$ contains individual covariates, including quadratic age, marital status, gender, country of birth, immigration category (family, refugee, economic, or other) at arrival, years of education at arrival, and official language knowledge (English or French) at arrival. The variable ψ_{i,t^-} denotes the firm pay premium at the individual's previous employer, where the lag t^- can refer to any earlier period of employment. The vector $\overline{\boldsymbol{x}}_{n(i),t-1}$ contains the averages of peers' characteristics—average individual fixed effects $\overline{\theta}_{n(i),t-1}$ estimated from equation (1), the proportion of females, the share by marital status (married, common law, separated, divorced, widowed and single), average age, and average age-squared—so δ captures contextual effects. The parameter $\lambda_{\ell(n(i)),t-1}$ is a fixed effect for the locale $\ell(n(i))$ containing neighborhood $n(i)$. It absorbs common shocks or sorting into larger residential areas. The parameter τ_t denotes year fixed effects, and ε_{it} is the error term. The coefficient ϕ measures the endogenous peer effect—the extent to which immigrants whose neighbors work at higher-paying firms themselves work at higher-paying firms in the subsequent year.

Model (2) is a reduced-form representation of several classes of theoretical models. Social interaction models in which individuals have a preference for conformity (e.g., Blume et al., 2015) suggest that individuals may adjust their job search and application behavior towards the prevailing needs of peer employers. Models with strategic complementarities in effort or job search (e.g., Calvó-Armengol et al., 2009) similarly predict that a higher incidence of high-quality jobs among peers increases the incentives or likelihood of securing such jobs oneself. From a search-theoretic perspective, peer effects may arise because information about vacancies, firm hiring standards, or workplace conditions are more readily available through social contacts (e.g., Montgomery, 1991; Beaman, 2016). In environments with imperfect information about worker productivity or firm–worker match quality, referrals from well-placed neighbors can also reduce asymmetric information, increasing both hiring probabilities and match quality (e.g., Dustmann et al., 2016). In all these cases, an estimate of $\phi > 0$ would indicate a combination of reduced search frictions and improved matching through local network channels.

2.2.2. *Main specification.* To assess whether the strength of neighborhood peer effects depends on shared identity between an immigrant and their peers, we extend equation (2) by partitioning the peer network into subgroups indexed by s, an indicator of whether the peer comes from the same identity group as the focal immigrant i, or from a different one:

$$\psi_{it} = \alpha + \gamma' \boldsymbol{x}_{it} + \nu \psi_{i,t^-} + \sum_s \phi_s\, \overline{\psi}^{s}_{n(i),t-1} + \sum_s \delta'_s\, \overline{\boldsymbol{x}}^{s}_{n(i),t-1} + \lambda_{\ell(n(i)),t-1} + \tau_t + \varepsilon_{it} \tag{3}$$

where $\overline{\psi}^{s}_{n(i),t-1}$ and $\overline{\boldsymbol{x}}^{s}_{n(i),t-1}$, defined analogously to equation (2), are the average firm premium and average characteristics, respectively, among type-s peers. When the identity marker is immigrant status, there are two s-types: fellow-immigrants and natives. When it is the country of birth, there are three peer groups: co-national immigrants, immigrants from other countries, and natives. Similarly with mother tongue. For immigrant-peers, the contextual vector additionally includes immigrant-specific composition and characteristics (shares by immigration category at arrival, average years of education at arrival, share with official language knowledge at arrival, and share of recent immigrants). This accounts for differences in the overall mix of same- and different-identity peers that may be correlated with unobserved factors affecting employer quality, such as the probability of social contact between groups, or neighborhood institutions that facilitate employment referrals within certain communities. In all cases, co-residing family members are excluded from peer sets.

Our interest lies in comparing the ϕ_s of same-identity peers and different-identity peers. A finding that the former is larger than the latter would be consistent with homophily in job-related information flows.

2.3. **Identification.** There are two main concerns pertaining to the identification of peer effects. The first, correlated effects, is our most pressing challenge so in this section, we describe how we tackle it in some detail. The potential second issue is the separate identification of endogenous peer effects and contextual effects. As we argue below, this is unlikely to be a major concern in our context.[1]

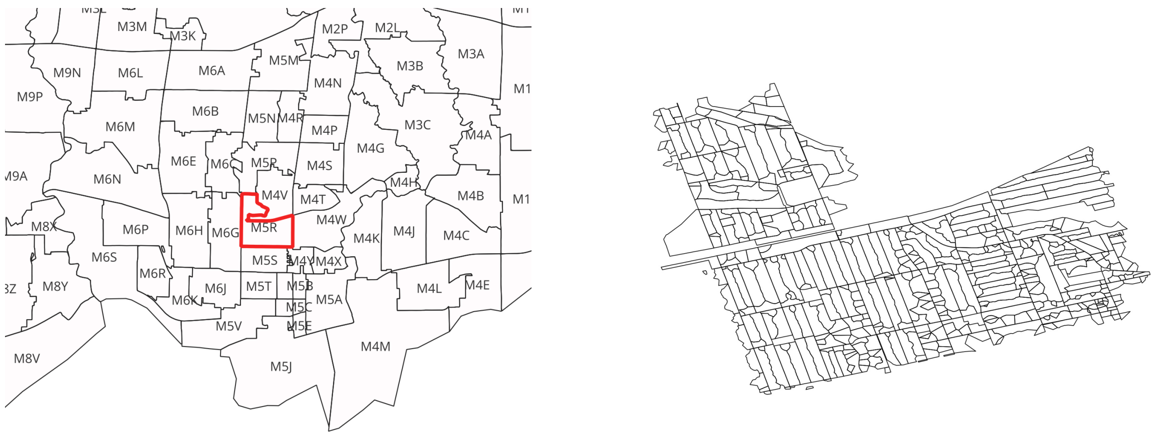
2.3.1. *Correlated effects.* The key identification challenge is correlated effects—the possibility that correlation among an individual's outcomes and that of their peers may be driven by endogenous choice of peers or common shocks (Manski, 1993). In our context, the former is manifested in neighborhood sorting. For example, people may select to live with peers who work at high-paying firms, with high-caliber skills or a strong work ethic that make them more likely to find jobs at these firms in the first place. The latter may be manifested in a common neighborhood-level shock. For instance, a bus line or road artery that makes it easier to commute to work or a daycare that makes it easier to work long hours at a high-powered job.

To address correlated effects, we rely on quasi-exogenous variation in assignment to neighborhoods—and by extension, peers—within larger residential locales. The basic idea is that people may choose to live in a particular locale based on individual characteristics or location characteristics. However, conditional on observable individual characteristics, exactly which neighborhood they live in *within* a given locale is plausibly exogenous.

We operationalize this by exploiting Canada's postal code structure, which we argue furnishes a natural way to address correlated effects while credibly capturing neighborhood-level social interactions. Specifically, postal codes—devised and maintained by the Canada Post Corporation—comprise 6 alphanumeric characters. The first three characters pertain to Forward Sortation Areas (FSAs); the last three characters, to Local Delivery Units (LDUs); and LDUs are nested in FSAs.[2] For example, the Toronto CMA has approximately 100,000 LDUs, which are nested within around 180 FSAs. Figure 1 presents an example of what this looks like in practice. Panel A presents a map of FSAs

[1] An additional issue is that there can be no "isolated" individuals in neighborhood networks. In other words, it cannot be the case that there is only one member of a particular group in a neighborhood since such an individual wouldn't have a neighborhood network. We ensure this through our sample restrictions, discussed in Section 3.4.

[2] The first character (a letter) denotes a large geographic area. For example, M denotes the City of Toronto. The second (numeric) character is always 0 for rural areas, and a positive integer for urban areas. The remaining characters have no discernible logic.



(A) FSAs in downtown Toronto

(B) LDUs in the *M5R* FSA

FIGURE 1. Example of neighborhoods and locales: LDUs in one downtown Toronto FSA

in downtown Toronto. Panel B zooms in on the (6-character) LDUs within the three-character FSA, *M5R*. This FSA, outlined in bold (red) in Panel (A) roughly coincides with what locals call “The Annex": a locale abutting the University of Toronto. Its population of 26,197 inhabitants according to the 2021 census is comparable to Toronto’s median FSA population of 26,128. Its large LDU count and structure also mirrors that of other FSAs in this area.

Boundaries of FSAs are constructed for ease of sorting and subsequent physical delivery of post. Within urban areas, the sorting feature means that each FSA is readily accessible by road, typically through a major artery. The physical delivery feature means that FSAs are geographically contiguous and contain addresses that are connected, often traversable by bicycle or foot. These features suggest that residents of an FSA have similar physical access to road and transportation networks; public goods and services such as schools, community centres and parks; and private goods and services such as shops and restaurants. As such, FSAs–almost by construction–capture an important range of individual motivations for sorting as well as sources of common shocks, making them a compelling measure of locale given our identification strategy.

LDUs within a given FSA are designed to facilitate hand-delivery of mail by postal workers. This means that, again almost by construction, each postal code contains a subset of blocks that are conducive to in-person interaction. This makes postal codes natural candidates for defining neighborhood networks. At the same time, the housing market was tight during our observation period. According to Statistics Canada, the vacancy rates in Toronto, Vancouver, and Montréal between 2001-2017 were 2.3%, 1.2%, and 2.7%, respectively. This means, even if one could choose a locality to live in, finding housing in a particular neighborhood was a low-probability event. Additionally, gathering information on neighborhood characteristics at such a granular level is challenging for prospective buyers and renters (Bayer et al., 2008; Baum-Snow et al., 2024). This is apparent in the map reported in Panel (B) of Figure 1 above, where the single *M5R* FSA contains around 400 LDUs–which mostly correspond to single housing blocks with an average population of around 60, according to the 2021 census.

Our identification strategy rests on the claim that conditional on locale, neighborhood assignment is plausibly exogenous. In Section 4, following Bayer et al. (2008) and Schmutte (2016), we furnish evidence to support this claim by showing that conditional on locale, there is little evidence that individuals are sorting based on observable characteristics. We also show that our baseline results go through when we include locale×time fixed effects, to allow for potential time-varying common shocks at the FSA level. A final issue is the possibility that there may be identity-specific common shocks. For example, a regulatory change may allow for easier entry into high-paying firms whose employees tend to come from particular countries or speak particular languages. This would result in an upward bias of the peer effect estimate for immigrants' shared identity networks. We account for this possibility in Section 7 by showing that our results are robust to country-of-birth×year fixed effects.

2.3.2. *Reflection problem.* Even with plausibly exogenous neighborhood assignment, identification of endogenous effects may not be assured because peer effects may be a reflection of peer characteristics that are correlated with peer outcomes, rather than the effect of peer outcomes *per se*. For example, people from a particular ethnic group may also have cultural advantages when it comes to labor market integration, or skills that are well-suited for the Canadian job market. This would lead to upward bias in their shared identity peer effects estimate.

The reflection problem is unlikely to be of concern in our setting for two reasons. First, $\overline{\psi}_{n(i),t-1}$ depends on complete work histories. Since this is predetermined it is not likely to be characterized by simultaneity (Schmutte, 2015; Cornelissen et al., 2017). This is buttressed by the use of lagged rather than contemporaneous peer networks. Second, our model relies on exclusive averaging and, as Lee (2007) has shown, with enough variation in group sizes, model (2) is identified. As we show in Section 3, our data satisfies this condition.

3. Data

This section describes the data, including data sources, sample construction, and descriptive statistics. Clarifying sample terminology upfront will be helpful. We refer to the sample used to estimate firm-specific earnings premiums from the AKM model as the *connected set* of workers and firms. Our core immigrant cohort, for whom we estimate peer effects using the linear social interactions model, is called the *analytic sample*; note that this sample consists exclusively of immigrants. For both the connected set and the analytic sample, we may be interested in *All* observations, or the subset of *job switchers*.

For everyone in the connected set, we are able to construct neighborhood peer networks. We refer to these as *neighbors* or *peers*. When we disaggregate these by *immigrant-peers* and *native-peers*, we refer to them as such, or as *immigrant neighbors* and *native neighbors*. Our main focus will be on the analytic sample's neighbors. However in this Section, for the purpose of comparison, we will describe average neighbor characteristics and aggregate neighborhood characteristics of not just the analytic sample, but also the connected set. In some tables, we compare the all observations in the respective samples to the subsample of job switchers; and when describing these for the connected set, we disaggregate the (sub)sample by immigrants and natives.

3.1. **Data source.** Our primary data source is the Canadian Employer-Employee Dynamics Database (CEEDD) for the years 2001-2017 (Statistics Canada, 2020). The CEEDD links administrative files to match employees and employers in the Canadian labour market, providing population-wide coverage of individuals and firms. Like most administrative data sets, the CEEDD contains a limited number of demographic characteristics, but includes information on age, gender, marital status, and province of residence. The core of the CEEDD is the T1 (individual tax file), which provides information on annual income from employment. By matching the T1 with the job-level T4 Record of Employment (ROE), we can identify the individual's main employer.[3]

3.2. **Connected set.** We impose four sample inclusion criteria on the core 2001-2017 CEEDD data. First, we only include Canada's three largest Census Metropolitan Areas (CMAs)—Toronto, Montréal and Vancouver—which, in 2024, accounted for 36% of the total Canadian population. CMAs are economically and socially integrated urban areas that closely resemble U.S. commuting zones. As stipulated by Statistics Canada requirements, they comprise adjacent municipalities centered around a population core, with a total population of at least 100,000 of which at least 50,000 living in the main urban center. We focus on these CMAs because they are sizable, and have substantial immigrant populations. The 2001 census recorded a CMA population of 4.7 million in Toronto, 3.4 million in Montréal, and 2.0 million in Vancouver, with immigrant population shares of 43.8%, 37.6%, and 17.9%, respectively. Additionally, these CMAs are immigrant hubs. In 2001 around 70% of landed immigrants in the country resided in these 3 CMAs.

The second sample inclusion criterion pertains to worker ages and locations. We focus on workers between the ages of 25 to 60 who report working or residing in these three CMAs, in that (i) the headquarters of their main employer during the year was located in the CMA; and/or (ii) they reported a residential address within the CMA in their tax returns. Since commuting is not uncommon, this allows us to be as comprehensive as possible in our estimation of firm-specific earnings premiums.

The third criterion is aimed at approximating full-time status. Ideally, we would want to estimate the two-way fixed effect model of equation (1) on full-time workers only. Unfortunately, like other administrative data sets such as Social Security earnings records in the U.S., the CEEDD does not report hours worked or any indication for full- versus part-time status. We therefore only include workers whose earnings from the main employer during each year are above a threshold, which reflects the hypothetical earnings of an individual working full time at minimum wage (Dostie et al., 2023).[4]

Finally, since we are interested in the *firm* premium, we do not include public sector employers. With these restrictions in place we are left with a CEEDD dataset containing approximately 250,000 unique employers in 2001 and 350,000 in 2017, representing industries across the spectrum. We use this connected set of workers and firms to estimate the firm-specific earnings premium—i.e. the

[3] As is often the case with firm-level tax data, information at the establishment level is unavailable.

[4] Specifically, we construct the threshold in each year of observation by taking the product of the Ontario minimum wage in that year; the average number of weeks worked in Ontario in 2001; and the average number of hours worked per week in Ontario in 2001. The latter two are obtained from Census data. To put this threshold in perspective, in 2001, it amounted to CAD 13,962. The choice of Ontario avoids sample selection based on institutional differences in provincial minimum wages: Ontario is the largest labor market in our data, and its threshold is broadly representative of the inter-provincial range of minimum wages during the study period. Moreover, the share of employment spells near the cutoff is small, and outcome variables are standardized. Our results are robust to the use of province-specific thresholds.

firm fixed effect—from the AKM model.[5] In this model, firm fixed effects are identified only within "connected sets", the networks of workers and firms linked through job moves. Since our focus is on CMAs exhibiting high worker mobility, the largest connected set in each CMA captures nearly the entire CEEDD population in Toronto, Montréal and Vancouver: 97% of workers and 95% of firms. This set comprises 17 million immigrant-year and 52 million native-year observations (Table 1).

3.3. **Analytic sample.** We construct the core immigrant sample of analysis from the connected set by taking advantage of the fact that the CEEDD has been matched to the Longitudinal Immigration Database (IMDB), which contains detailed information on all immigrants who entered Canada since 1980.[6] Following Picot and Piraino (2013) and Dostie et al. (2023), among others, we categorize individuals as "immigrants" if they appear in the IMDB; "natives" are individuals who are not in the IMDB. In addition to the basic demographics mentioned earlier, the IMDB has detailed information on immigrants at entry, including education, official language knowledge, immigration category (economic, family, refugee, other), country of birth, and language.

Our analytic sample—a subset of immigrants from the connected set, for whom we estimate peer effects—satisfies five inclusion criteria, in addition to those described in Section 3.2. First, we restrict attention to immigrants who arrived in Canada between 1996 and 2001. This ensures that we study a cohort of recent immigrants, observed within five years of arrival, who are likely to have relatively weak pre-existing ties. Second, they must have lived in one of the three CMAs for at least one year between 2001 and 2017, which is necessary to construct neighborhood peer networks (Section 3.4). Third, they must be between ages 25 and 44 at the start of the observation period, so that the oldest in the sample are 60 by its end, reducing concerns about retirement effects.

Fourth, they must have at least two immigrant workers and one native worker in their neighborhood. This requirement, together with exclusive averaging, satisfies the "no isolation" condition and allows us to construct networks of immigrant and native neighbors for each focal immigrant. Finally, we require that each locale contains at least two neighborhoods. This restriction ensures within-locale variation, which is central to our identification strategy.

The final analytic sample, which satisfies these inclusion criteria, comprises roughly 900,000 individual-year observations, constituting about 7% of the original CEEDD population for the Toronto, Montréal and Vancouver CMAs. Around 60% of these immigrants reside in Toronto, 15% in Montréal, and 25% in Vancouver.

Table 1 presents descriptive statistics for the analytic sample and, for comparison, all immigrants and all natives in the connected set. These and all subsequent summary statistics are rounded to comply with Statistics Canada's confidentiality vetting process. Immigrants in the analytic sample work at somewhat higher-quality employers on average—measured through average AKM firm FE estimates in the first row—though their firm premiums are below natives'. Job switching is more common in the analytic sample (20% of observations) than among immigrants or natives in the connected

[5]Two additional criteria are that (i) information regarding sex be non-missing in both tax records and IMBD, and (ii) real value added per worker be larger than CAD 100. Very few observations do not satisfy these requirements.

[6]Technically, the IMDB has tracked immigrants since 1952. However, detailed information, including immigration category, language, and education was only made available from 1980 on. It has also tracked non-permanent residents (NPRs) since 1980. However, since NPRs, typically holding study permits and are not engaged in full-time employment, or hold work permits that are restricted to specific employers, we exclude them from our analysis. See Statistics Canada (2024).

	Analytic Sample		**Connected set**			
	All	**Job Switchers**	**All**		**Job Switchers**	
			Immigrants	**Natives**	**Immigrants**	**Natives**
Average firm pay premium	-0.007	-0.002	-0.026	0.009	-0.025	-0.003
Job switches	20%	100%	11%	11%	100%	100%
Female	43%	40%	45%	45%	41%	42%
Age in 2001	34	34	33	35	32	33
Married	81%	80%	72%	64%	70%	61%
Years of education	15	15	12		12	
Officia language knowledge	74%	76%	66%		68%	
N.Obs.	900,000	180,000	17.3 million	52.4 million	1.5 million	4.4 million
N.Workers	120,000	90,000	2.7 million	7.6 million	890,000	2.5 million
N.Firms	60,000	40,000	490,000	650,000	180,000	300,000

TABLE 1. Descriptive statistics: Individual characteristics. *Notes.* This table presents descriptive statistics for the analytic sample and the connected set. For the analytic sample, we report summary statistics for all observations in the sample and for the subsample of observations following a job switch. Similarly, we report summary statistics for all observations in the connected set and for the corresponding subset of job switchers, separately by immigrant status. Reported statistics include the average firm pay premium ($\psi_{j(i,t)}$) from Eq.1; the share of observations that follow a job switch; the share of women; average age in 2001; the share of married individuals; and average years of education and official language knowledge at arrival, for immigrants. All figures are rounded to comply with Statistics Canada's confidentiality vetting process; the same convention applies to all other tables.

set (11%). The female share is slightly lower in the analytic sample, consistent with the full-time earnings threshold and the post-switch subset modestly reducing women's representation. Education and official language knowledge at arrival are reported only for immigrants and are higher in the analytic sample than in the connected set. Marriage rates are also higher in the analytic sample although, in general though, immigrants in the connected set are more likely to be married than natives.

3.4. **Neighbors and neighborhoods.** For each immigrant in the analytic sample, and for each year of observation, we construct neighborhood-level peer networks. We first identify peers as *all* individuals in the connected sample who report a residential address in the same 6-character postal code as the focal immigrant in their annual tax return, and who do *not* belong to the same family as the immigrant as reported in the immigrant's tax records. These peer networks comprise 16.6 million observations.

Table 2 provides the analog of the individual-level descriptives in Table 1, but for neighborhood peers of immigrants in the analytic sample. Since we disaggregate peer effects by immigrants and natives in our analysis later on, we do the same here for the descriptive statistics. Statistics are very similar for all observations and the subsample of job switchers, except that the latter are slightly older. Native-peers are employed in higher-quality firms than immigrant-peers, consistent with the immigrant–native gap in employer quality already seen in Table 1, and with Dostie et al. (2023). Overall, the size distribution of immigrant-peer and native-peer network are quite similar, characterized by continuous mass and common support (see Appendix Figure A1).

	All			Job switchers		
	All	Natives	Immigrants	All	Natives	Immigrants
Average firm pay premium	-0.016	-0.006	-0.028	-0.015	-0.004	-0.028
Female	47%	48%	45%	47%	48%	45%
Age in 2001	32	32	32	34	34	34
Married	65%	58%	72%	64%	57%	71%
Years of education			12			12
Official language knowledge			68%			69%
N.Obs.	16.6 million	8.7 million	7.9 million	5.9 million	3.1 million	2.8 million

TABLE 2. Descriptive statistics: Neighborhood-peer characteristics of analytic sample. *Notes.* This table presents descriptive statistics for the peers of individuals in the analytic sample and for the peers of immigrants in the job switchers subsample. We report summary statistics for all peers, and separately by peer immigrant status. Reported statistics include the average firm pay premium ($\psi_{j(i,t)}$) from Eq.1; the share of observations that follow a job switch; the share of women; average age in 2001; the share of married individuals; and average years of education and official language knowledge at arrival, for immigrants.

	Analytic sample		Connected set			
			All		Job Switchers	
	All	Job Switchers	Immigrants	Natives	Immigrants	Natives
# Neighborhood-year observations	488,000	141,000	3.2 million	8.1 million	800,000	2.3 million
# Neighborhoods	68,000	49,000	365,000	704,000	199,000	466,000
# Neighborhoods per locale (mean)	678	665	689	723	673	688
Neighborhood characteristics (average)						
Total population	98	121	68	46	94	80
Immigrant share	47%	49%	32%	14%	41%	18%
Average employment income	$44,000	$41,000	$46,000	$46,000	$44,000	$47,000
Average T4 income from main employer	$42,000	$39,000	$44,000	$44,000	$42,000	$45,000

TABLE 3. Descriptive statistics: Neighborhood & neighborhood-peer characteristics of analytic sample & connected set. *Notes.* This table presents descriptive statistics for the residential neighborhoods of the analytic sample and of the connected set from Eq.1. For the analytic sample, we report neighborhood-level summary statistics for all observations in the sample and for the subsample of observations following a job switch. Similarly, we report summary statistics for all observations in the connected set and for the corresponding subset of job switchers, separately by immigrant status. Reported statistics include the average total population, immigrant share, average employment income, and average income from the main employers, at the neighborhood level.

Table 3 provides neighborhood-level descriptives for the analytic immigrant sample and the connected set, with the latter disaggregated by immigrant and native status. On average, neighborhoods in the analytic sample are less wealthy than those of both immigrants and natives in the connected set, with lower employment and T4 incomes. Locales of both immigrants and natives are similar in terms of the number of neighborhoods they contain. The analytic sample's neighborhoods are more populous on average, and immigrant shares are higher in the analytic sample's neighborhoods than in either connected-set counterpart. These differences are also present in the job-switcher subsample, where analytic-sample neighborhoods again show lower incomes, larger populations, and higher immigrant shares. Taken together, these patterns indicate that the analytic sample's neighborhoods are broadly comparable to those in the connected set, but tilt toward being larger, more immigrant-dense, and less wealthy—features that reinforce the relevance of our analysis for immigrant-concentrated urban contexts.

To explore the effect of shared national identity, we disaggregate immigrant-peers in each neighborhood by country of birth. Specifically, for each immigrant in our analytic sample, we group other immigrants in their neighborhood according to whether they have the same country of birth as the focal immigrant, or come from a different country of birth. The challenge we face is that immigrants in this data originate from over one hundred different countries, many of which have small absolute numbers of immigrants. Hence, immigrants from “low intake" countries often fail to satisfy the no isolation requirement, or are characterized by very small fellow-national immigrant networks that lack meaningful variation necessary for identification.

For this part of our analysis, we therefore impose a further sample restriction to ensure that co-national neighborhood immigrant networks exist, and are large enough to make meaningful statistical inference. Specifically, we restrict the analytic sample to immigrants that come from the ten most common origin countries in each CMA—a total of 18 countries between them—over our period of observation.[7] Immigrants from these countries represent around 66% of the full analytic sample.

We conduct an analogous exercise for co-linguists by disaggregating immigrants in each neighborhood according to whether they share a mother tongue with the focal immigrant or not. Again, there hundreds of different languages so we restrict our sample to immigrants with the ten most common mother tongues upon arrival in each CMA—a grand total of 15 languages.[8] Immigrants with these mother tongues represent around 69% of the full analytic sample.

4. Identification: Supportive Evidence

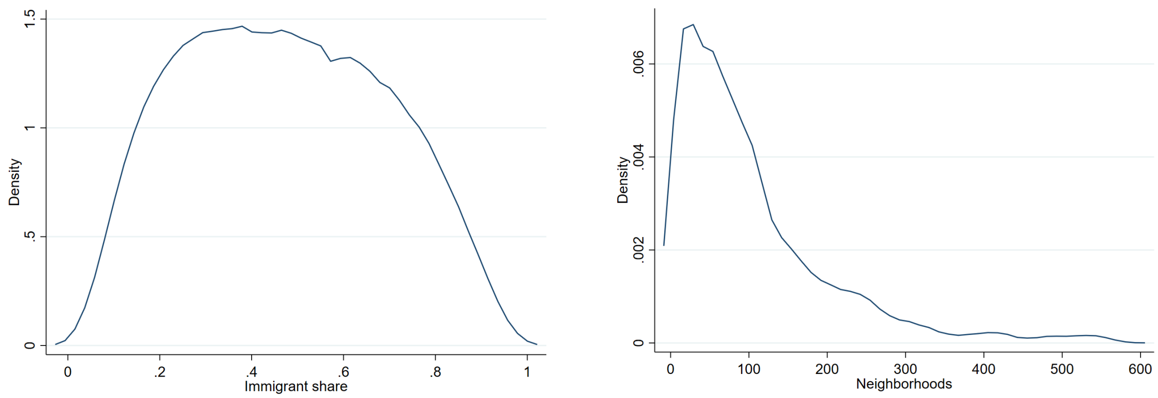
In this section, we provide supporting evidence for identification of peer effects along several dimensions. We first show that immigrant- and native-peer effects can in principle be identified because most neighborhoods contain a mix of immigrants and natives, and locales contain multiple neighborhoods. Next—although neighborhoods of residence are not randomly assigned—we provide support for the identifying assumption that, conditional on locale, there is negligible sorting based on observables. Finally, we examine residential mobility and show that job switches are not accompanied by neighborhood moves, nor do movers select neighborhoods based on the job characteristics of future neighbors.

A first concern is that immigrant- and native-peer effects cannot be separately identified if neighborhoods are too homogeneous or if locales contain only a single neighborhood. Figure 3 shows that neither problem arises. Panel A documents substantial interior mass in the distribution of immigrant shares across neighborhoods: most contain both immigrants and natives, with relatively few all-immigrant or all-native enclaves. Panel B shows wide variation in the number of neighborhoods

[7] From 2001-2017, these countries were India, China, Philippines, Pakistan, Hong Kong, Jamaica, Romania, Sri Lanka, Russia, and Iran in the Toronto CMA; France, Algeria, China, Romania, Morocco, Haiti, Philippines, India, Russia and Sri Lanka in the Montréal CMA; and China, Philippines, India, Hong Kong, United Kingdom, Iran, Taiwan, Japan, Romania and South Africa in the Vancouver CMA.

[8] These are English, Mandarin, Cantonese, Chinese, Punjabi, Urdu, Tamil, Tagalog, Russian, and Romanian in the Toronto CMA; French, Arabic, Spanish, Romanian, Russian, Creole, English, Mandarin, Tagalog and Chinese in the Montréal CMA; and Tagalog, Mandarin, English, Punjabi, Cantonese, Chinese, Russian, Spanish, Japanese and Romanian in the Vancouver CMA.

per locale, ensuring that peer effects can be identified from within-locale contrasts rather than from across-locale differences. In addition this variation also satisfies the sufficiency condition posited in Lee (2007) for tackling the reflection problem.[9]



(A) Immigrant share of neighborhood population

(B) Number of neighborhoods by locale

FIGURE 2. Immigrant share and neighborhood size distributions. *Notes.* Panel A shows the distribution of neighborhood-level immigrant shares across the residential neighborhoods of immigrants in the analytic sample. Panel B shows the distribution of the number of neighborhoods per locale within the same sample. The distributions are smoothed to comply with Statistics Canada's confidentiality vetting process; the same convention applies to all other figures.

A second concern is sorting into neighborhoods. The identification strategy assumes that, within a given locale, an individual's neighborhood choice is plausibly exogenous. A testable implication is that, conditional on locale, immigrants should not sort into neighborhoods based on observables. We assess this following Bayer et al. (2008) and Schmutte (2015). Concretely, we randomly draw one person from the neighborhood of each individual in the analytic sample. We regress an observed characteristic of the randomly drawn individual on the corresponding neighborhood average (excluding the selected individual and their family).

Table 4 report R^2's from this exercise. In Columns 1-4 we run this exercise on all peers; for this sample we have data on sex, age, marital status, immigrant status, and the residual from model (1). In Columns 5-8 we repeat this exercise for the subset of immigrant-peers, for whom we have additional measurements on years of education, official language knowledge at arrival, and an indicator for arrival within the past ten years. As expected, without fixed effects (Columns 1 and 5), neighbors' averages strongly predict the randomly selected individual's own characteristic—evidence of nonrandom residential choice at broad geographic scales.

Crucially, once we condition on locale (Columns 2 and 6), explanatory power collapses: R^2 values fall close to zero across characteristics, including immigrant-specific covariates such as education and official language at arrival. Adding year fixed effects (Columns 3 and 7) and locale-by-year fixed effects (Columns 4 and 8) does not substantively change this conclusion. In our main specifications,

[9]A separate concern regarding sample size is that, at such granular level, neighborhood networks may be small, and with small networks measurement of average characteristic may be noisy—possibly attenuating peer effects estimates. We address this in Section 7, by showing that our results are robust even when we restrict attention to immigrants with at least five immigrant neighbors and five native neighbors.

	Peer sample				Immigrant-peer subsample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Native	0.519	0.027	0.021	0.021				
Female	0.446	0.001	0.001	0.001	0.391	0.001	0.001	0.001
Age	0.951	0.016	0.007	0.007	0.954	0.014	0.002	0.002
Married	0.650	0.021	0.021	0.020	0.691	0.009	0.009	0.009
Years of education					0.857	0.003	0.003	0.003
Recent immigrant					0.341	0.028	0.002	0.001
Official language knowledge at arrival					0.667	0.005	0.005	0.005
Residuals from Eq. 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Locale FE	No	Yes	Yes	No	No	Yes	Yes	No
Year FE	No	No	Yes	No	No	No	Yes	No
Locale-Year FE	No	No	No	Yes	No	No	No	Yes

TABLE 4. Sorting within locales. *Notes.* Each row reports the R^2 from regressions of a randomly selected individual's characteristic on the neighborhood mean of that same characteristic (excluding the individual and co-residing family). We estimate these models in the full sample (natives and immigrants) and in the immigrant subsample. Columns 1 and 5 report univariate R^2 without fixed effects; Columns 2 and 6 add locale fixed effects; Columns 3 and 7 add year fixed effects; Columns 4 and 8 add locale-by-year fixed effects.

we therefore include (time-invariant) locale fixed effects to absorb sorting within locales, as well as year FE.

A third, related, concern is that workers may move into neighborhoods where their future colleagues already reside, rather than their neighbors subsequently becoming their colleagues. If this happens, then the observed correlation between a worker's outcomes and the characteristics of their neighbors may not reflect a causal neighborhood effect on employment outcomes. Instead, it may simply reflect sorting or selection based on job-related factors. While our social interactions model already addresses potential reverse causality through its lag structure, we undertake two additional exercises to further allay this concern.

First, we examine the timing of residential moves across neighborhoods around the time of a job switch, controlling for individual characteristics as well as year and individual fixed effects by estimating the following model:

$$moved_{it} = \alpha_i + \sum_{k=-3,k\neq 0}^{k=3} \beta_k D_{(t-t_i=k)} + \gamma' x_{it} + \tau_t + \varepsilon_{it} \tag{4}$$

where $moved_{it}$ is an indicator equal to one if individual i changed neighborhoods between years $t-1$ and t; α_i denotes individual fixed effects capturing time-invariant differences across workers; $D_{(t-t_i=k)}$ is a set of event-time dummies equal to 1 if calendar year t is k years away from the year of the job switch t_i, for $k \in \{-3,-2,-1,1,2,3\}$, with $k = 0$ corresponding to the switch year; x_{it} is a vector of time-varying controls, including a quadratic in age and marital status; τ_t and calendar-year fixed effects; and ε_{it} is an error term.

The results, shown in Figure 3, suggest that focal immigrants are not significantly more likely to relocate across neighborhoods following a job switch.

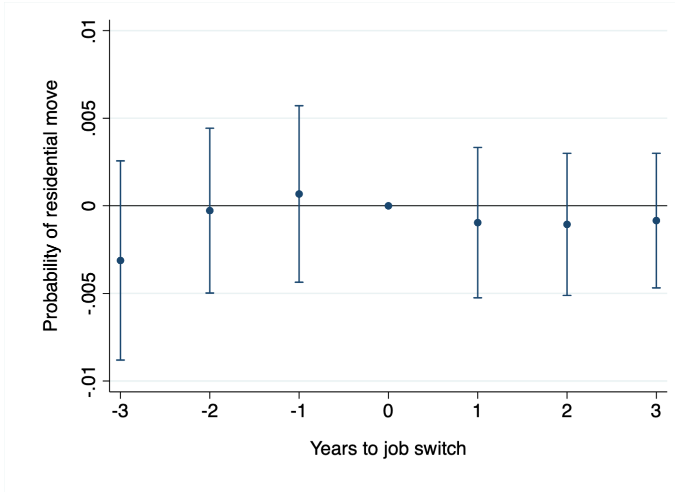


FIGURE 3. Probability of residential moves around a job switch. *Notes.* The figure plots estimates of β_k from Eq. 4—which capture the probability of changing neighborhoods around the time of a job switch—together with 95% confidence intervals. The regression include individual fixed effects, year fixed effects, and controls for age and marital status. Sample: immigrants in the analytic sample.

	Peer sample				**Immigrant-peer sample**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agriculture, forestry, fishing, hunting	0.002	0.001	0.001	0.001	0.003	0.001	0.001	0.001
Mining, utilities, construction	0.026	0.001	0.001	0.000	0.008	0.001	0.001	0.001
Manufacturing	0.140	0.003	0.001	0.001	0.093	0.002	0.001	0.000
Wholesale and retail trade, transportation	0.139	0.000	0.000	0.000	0.056	0.000	0.000	0.000
Information, finance, insurance, etc.*	0.290	0.003	0.001	0.001	0.173	0.002	0.001	0.001
Education, healthcare, social assistance	0.110	0.002	0.001	0.001	0.028	0.001	0.000	0.000
Arts, entertainment, hospitality	0.019	0.000	0.000	0.000	0.009	0.001	0.001	0.000
Other services	0.012	0.000	0.000	0.000	0.005	0.000	0.000	0.000
Firm size	0.115	0.000	0.000	0.000	0.038	0.000	0.000	0.000
Commuting distance	0.107	0.000	0.000	0.000	0.039	0.000	0.000	0.000
Locale FE	No	Yes	Yes	No	No	Yes	Yes	No
Year FE	No	No	Yes	No	No	No	Yes	No
Locale-Year FE	No	No	No	Yes	No	No	No	Yes

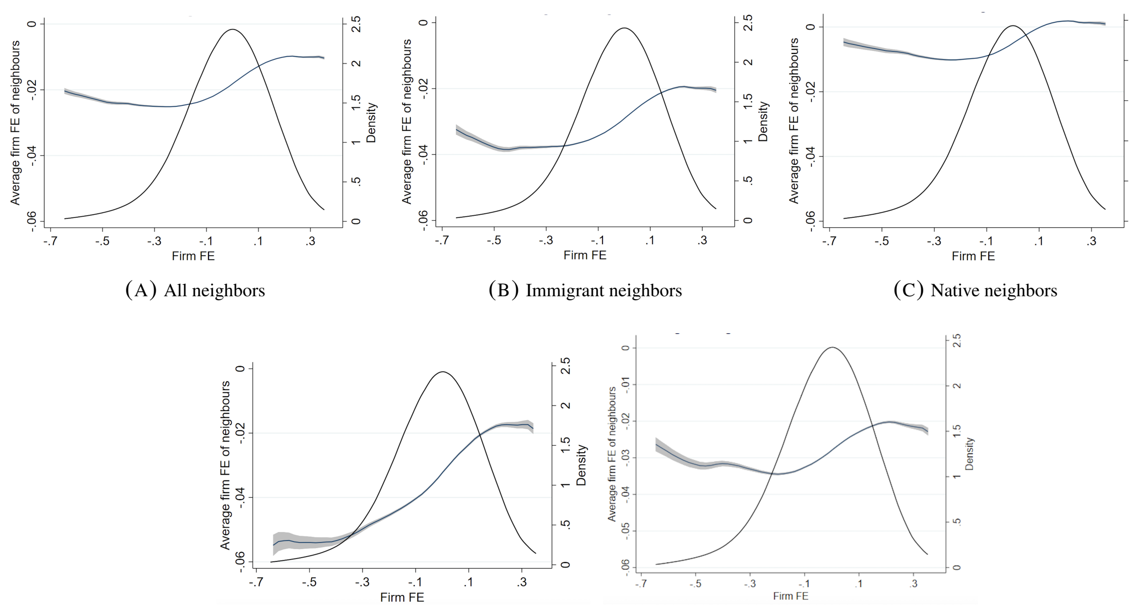
TABLE 5. Sorting within locales: movers. *Notes.* This table presents the R^2 for a set of regressions with a characteristic for a randomly selected individual among the subset of residential movers on the left-hand side, and the current average of that variable for their future neighbors on the right-hand side. * Information, finance, insurance, real estate, professional, scientific and technical services, management of companies, administrative services

Second, we conduct an exercise analogous to that in Table 4, to provide supportive evidence that—conditional on locale and time FE—neighborhood choice is not based on the job characteristics of future neighbors. Specifically, we restrict attention to the peers of our analytic sample who switched neighborhoods. From this subsample of neighborhood movers, we randomly select one individual per neighborhood. Using this randomly selected subset, 5, allay concerns of sorting on this basis.

5. Main Results

In this section, we report neighborhood peer effects estimates on the firm pay-premiums of immigrants (from the analytic sample). We begin by briefly describing the nonparametric relationship between individual firm-specific earnings premiums and that of their neighbors. Next, we report peer effect estimates of different neighborhood peer groups, beginning with the full neighborhood network (Model 2) and then disaggregated by immigrant- and native-peers (Model 3). We show that peer effects are driven by immigrant neighbors, and that positive peer effects are consistent with greater employer mobility rather than improved job stability. Finally, we investigate the presence of homophily by immigrants' country of birth and mother tongue.

5.1. **Descriptive evidence.** Figure 4 traces the relationship between an individual's firm pay premium (x-axis) and the average premium of their neighborhood peers (y-axis), estimated using a local polynomial regression of the latter on the former. Panel A (all neighbors) shows a weak positive association, strongest around the middle of the premium distribution. Panels B and C split peers by immigrant status: both slopes are positive, but the association is clearly stronger for immigrant-peers than for native-peers.



(A) All neighbors (B) Immigrant neighbors (C) Native neighbors

(D) Immigrants: same birth country (E) Immigrants: other birth countries

FIGURE 4. Firm pay premium of individuals and their neighbors. *Notes.* The figures show the semiparametric relationship between immigrants' firm pay premium and the average premium of their peers (measured on the left y-axis) for individuals in the 1st–99th percentiles of the firm pay premium distribution. Shaded gray areas indicate 95 percent confidence intervals. Each figure also shows the distribution of individual firm pay premiums (right y-axis).

The bottom row restricts the sample to immigrant-peers from the top countries of birth and separates co-nationals from other immigrants. Panel D (co-nationals) shows a steeper positive association than Panel E (other immigrant origins), indicating stronger alignment in employer quality with co-nationals than with immigrants from other countries. Taken together, these correlations are consistent with positive neighborhood peer effects, especially among immigrant neighbors of shared identity.

5.2. **Peer effects.** This section presents peer effect estimates. We start by estimating the peer effect, ϕ, from the benchmark Model (2) for the full neighborhood network, and move quickly to disaggregating this network by shared identity—Model (3)—beginning with fellow immigrant- vs. native neighbors. Next, we disaggregate immigrant neighbors into finer and arguably more salient dimensions of common identity—specifically, whether they share the same country of birth and mother tongue.

Average firm pay premium	*Dependent variable: Firm pay premium* (1)	(2)	(3)	(4)	(5)
	Panel A: all peers				
All peers	0.275***	0.171***	0.097***	0.082***	0.066***
	(0.015)	(0.011)	(0.001)	(0.001)	(0.009)
N.Obs.	900,000	900,000	900,000	900,000	900,000
	Panel B: immigrant and native peers				
Immigrant peers	0.125***	0.081***	0.049***	0.041***	0.034***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)
Native peers	0.080***	0.047***	0.016***	0.001*	0.007
	(0.009)	(0.007)	(0.006)	(0.006)	(0.005)
Test: Immigrant peers = Native peers					
F	13.380	12.625	13.745	12.551	10.994
Prob > F	0.000	0.000	0.000	0.000	0.001
N.Obs.	900,000	900,000	900,000	900,000	900,000
Year FE	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Locale FE	No	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes	Yes
Previous employer firm pay premium	No	No	No	No	Yes

TABLE 6. Peer effects on immigrants *Notes.* Panel A presents coefficient estimates for ϕ in model 2, while Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls include quadratic age, sex, marital status, years of education and official language knowledge at arrival, immigration category, and country of birth. Contextual effects include the average age and average square of age among the individual's neighborhood peers, the share of women, the share of peers by marital status, and the average individual fixed effects from model 1 among the individual's peers. In panel B, contextual effects also include average years of education, share by official language knowledge at arrival, share by immigration category, and share by country of birth, among immigrant-peers. p-values of the test for $\overline{\psi^1}_{j,t-1} = \overline{\psi^0}_{j,t-1}$ are presented in the bottom row. The number of observations is rounded to comply with Statistics Canada's confidentiality vetting process; the same convention applies to all other results tables. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 presents peer effect estimates for the full neighborhood network (Panel A) and the neighborhood network disaggregated network by immigrant status (Panel B).[10] Column 1 of Panel A shows a raw correlation of 0.275 between own and neighbors' firm premia, correcting only for year FE. Adding individual controls in Column 2 lowers this coefficient sharply, suggesting that the raw correlation reflects neighborhood sorting on observable characteristics. When we account for this explicitly by including locale FE in Column 3, the coefficient falls by three-quarters. In Columns 3-5—which all include locale FE—the estimated peer effect remains largely unchanged, confirming that identification comes from within-locality variation in peer quality. Column 4 indicates that adding peer characteristics—their average firm pay-premiums, proportion of females, the share by marital status, average age, and average age-squared—does not substantively change the coefficient, suggesting that the peer effect estimates are not simply picking up contextual composition. In Column 5, we include the immigrant's prior firm premium.[11] Consistent with job ladders, the coefficient on that variable (not shown) is positive, and the peer effect estimate falls further to 0.066.

Column 5 represents our fully saturated model. Qualitatively the 0.066 estimate shows that, conditional on year FE, individual covariates, locale FE, neighborhood composition, and prior employer, immigrants whose peers work in higher-quality firms tend themselves to be employed in higher-quality firms. The point estimate in Column 5 suggests that a one-standard-deviation (= 0.340) increase in neighborhood peer quality raises own firm quality by about 0.022—translating to a meaningful bump in earnings of 2.3%.

Panel B reports peer effect estimates for Model (3), where the neighborhood network is disaggregated by immigrant status.[12] Columns 1–4 (with additional controls for immigrant characteristics and neighborhood composition in column 4) show the same attenuation pattern as Panel A. In Column 5, the coefficient on immigrant neighbors' average firm premium is 0.034, implying a 1.2% earnings increase following a one-standard deviation increase in immigrant-peer quality. By contrast, the coefficient on native-peers is close to zero and statistically insignificant. As the F-test at the bottom of Panel B indicates, the difference between immigrant- and native-peer effects is statistically significant regardless of specification.[13] The evidence therefore points to positive neighborhood peer effects operating through immigrant-peers.

Figure 5 investigates peer effects among immigrants along two salient markers: nationality and language. It presents coefficient estimates for three separate regressions for the fully saturated

[10]Estimates for peer effects in this and all subsequent tables are for one-lagged peer averages. Appendix Table B1 shows that the results are qualitatively identical for contemporaneous, as well as twice-lagged peer averages.

[11]Controlling for prior firm premium also mitigates concerns that peer effects simply reflect lower average employer quality among immigrants and co-nationals. Controlling for baseline employer quality ensures that the estimated effect reflects peer-quality variation rather than persistence in initial conditions.

[12]These estimates are obtained from a regression that includes both variables jointly, as in Model 3. They are therefore conditional effects and not a simple disaggregation of Panel A, which uses the average of all neighbors as a single regressor. Because immigrant and native neighbor quality are correlated, the coefficients in Panel B do not sum to the Panel A estimate.

[13]Appendix Table B2 reports fully saturated estimates separately for Toronto, Montréal, and Vancouver. While magnitudes vary somewhat across cities (they are similar in Toronto and Vancouver, and more muted in Montréal) the immigrant-peer coefficient is positive in each CMA, and the qualitative contrasts documented in Table 6 persist: immigrant-peers matter and native-peers matter little by comparison.

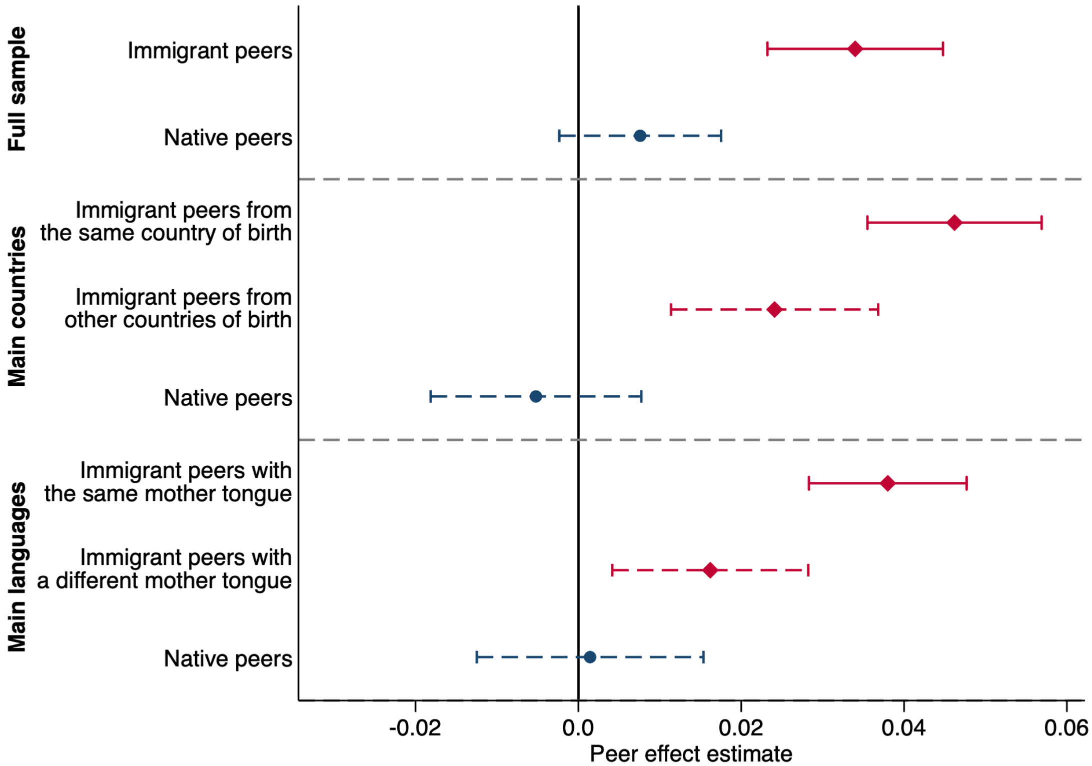


FIGURE 5. Homophily in neighborhood peer effects. *Notes.* Each set of plots in this figure shows peer effect coefficient estimates for the fully saturated model, along with their 95% confidence intervals. Estimates for different regressions are separated by a dashed line. The first two sets of estimates graphically depict point estimates from Column of Panel A and B, respectively in Table 6. The remaining sets are for co-nationals vs. others; and co-linguists vs. others. See Appendix Table B3.

model.[14] The top panel presents the same estimates as Table 6 Panel B—the immigrant vs. native-peer effects comparison—highlighting again that peer effects on immigrants run through fellow-immigrants rather than natives. The middle panel restricts the analytic sample to immigrants from the largest origin countries, disaggregating their neighborhood networks into co-national immigrants, non-co-national immigrants, and natives. The bottom panel does the same thing for the largest language groups, except by co-linguists rather than co-nationals. In both cases, positive, statistically significant peer effects are exerted by both same- and different-identity immigrant-peers. However, coefficient estimates are almost twice as large for those who share the same country of birth or the same language than those who do not, a statistically significant difference.[15] Peer effects of natives remain close to zero and statistically insignificant. The results are consistent with neighborhood peer effects being shaped by homophily: immigrants stand to benefit most from peers with whom they share a similar cultural background and a common language.

[14]Appendix Table B3 provides detailed results from which Figure 5 was constructed. Analogous estimates for the switchers subsample in Appendix Table B4 display the same ordering by identity, but are substantially less precise owing to small cell sizes so we refrain from over-interpreting them.

[15]Aggregating origins to world areas yields larger coefficients; we discuss why in Section 7.

Average firm pay premium	(1)	(2)	(3)	(4)	(5)
	Panel A: probability of staying in job				
Immigrant peers	-0.011	-0.008	0.002	0.006	0.007
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Native peers	0.001	-0.010	-0.006	-0.002	-0.002
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
N.Obs.	800,000	800,000	800,000	800,000	800,000
	Panel B: firm pay premium for job switchers				
Immigrant peers	0.098***	0.063***	0.035***	0.028***	0.017**
	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)
Native peers	0.086***	0.050***	0.021**	0.016	0.010
	(0.013)	(0.011)	(0.010)	(0.010)	(0.008)
Test: Immigrant peers = Native peers					
F	0.518	0.745	0.898	0.690	0.300
Prob > F	0.472	0.389	0.344	0.407	0.584
N.Obs.	100,000	100,000	100,000	100,000	100,000
Year FE	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Locale FE	No	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes	Yes
Previous employer firm pay premium	No	No	No	No	Yes

TABLE 7. Stayers and switchers. *Notes.* Panel A presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is an indicator for retention at the same employer in $t + 1$. Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls and contextual effects are the same as in Panel B of Table 6. p-values of the test for $\bar{\psi}^1_{j,t-1} = \bar{\psi}^0_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

A natural question to ask is whether these peer effects operate primarily through job mobility. If immigrants remain with the same employer, variation in their own firm premium is limited, so any observed association must reflect stability rather than movement. By contrast, if immigrants switch employers, peer effects may be reflected in the quality of new job matches. Prior work emphasizes mobility as the central channel. Early studies highlight residential networks as conduits for job information (Topa, 2001; Bayer et al., 2008), and Schmutte (2015) shows for U.S. job switchers that peer exposure predicts the quality of subsequent matches. More recent contributions also stress mobility and referrals (Cornelissen et al., 2017; Glitz and Vejlin, 2021), while Dustmann et al. (2023a) show how social identity conditions immigrant labor market trajectories. Evidence from refugee placement and integration (Martén et al., 2019; Stips and Kis-Katos, 2020; Caiumi and Simonsen, 2025) further underscores the role of mobility channels.

Table 7 explores which of these two channels—more job stability or upward job mobility—accounts for positive peer effects. Panel A investigates the first of these channels by presenting estimates for the association between immigrant- vs. native-peer quality on the probability of the immigrant staying at the same employer. The estimate is close to zero and statistically insignificant across specifications.[16] This suggests that more job stability is unlikely to account for positive peer effects.

Panel B explores the upward job mobility channel by furnishing estimates for Model 3 on the subsample of observations in the periods directly following immigrants' job switches.[17] The positive peer effect estimates indicate that higher quality immigrant-peers are associated with more upward job mobility whereas—once contextual effects are incorporated—native-peers are not.

Interpreted within a job search framework (Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002), the Column 5 estimates suggest that the benefits of high-quality peer networks operate primarily through employer changes. This estimate, though economically meaningful, is smaller than the full neighborhood peer effect reported by Schmutte (2015) for a single cross-section of an otherwise comparable US sample. As we show in the next section this difference, to some extent, reflects the inclusion of family members in neighborhood networks.

Interestingly, Schmutte (2015) shows that the estimated peer effect parameter for job switchers can also be interpreted as the share of job offers that come through the network. This interpretation holds in a setting where job offers arrive through both formal and network channels, and where network quality affects only the distribution of offers from the network—not the arrival rate or quality of formal offers (See also Ioannides and Loury, 2004). Interpreted through this lens, the estimate from Panel B Column 5 suggests that approximately 2% of job offers are mediated through an immigrant's immigrant-peer network.

Taken together, the results in this section show that neighborhood peer effects are robust to a demanding set of controls. They are concentrated among immigrant-peers not native-peers, and are amplified when peers share a national or linguistic identity—attributes which are likely to facilitate relevant information sharing. Peer effects do not seem to operate through job stability but instead through mobility, which is consistent with higher-quality immigrant neighbors facilitating moves to higher-quality firms.

6. Mechanisms and Heterogeneity

This section probes the main results by asking whether natives also enjoy peer effects, whether non-ethnic markers of shared identity also matter, and which immigrants benefit most from peer effects. Four exercises guide the analysis. First, we estimate peer effects for natives as the focal group, to assess whether the patterns observed for immigrants reflect group-specific influences or general neighborhood social interactions. Second, we assess the role of family ties, underscoring the importance of distinguishing neighbor- from close family-networks. Third, we examine whether homophily extends beyond national and linguistic identity to two salient non-ethnic markers of identity, namely, gender and recency of arrival. Finally, we investigate heterogeneous responses by focal immigrant characteristics such as age, education, and immigration category.

[16]Appendix Table B5 shows that the null effect is not masking heterogeneity: peers do not seem to affect job stability in either high- or low-premium firms.

[17]Schmutte (2015) shows that results for switcher sub-samples are robust to controlling for endogenous selection into job-to-job mobility.

6.1. **Natives.** The first exercise asks whether the peer effects between immigrants reflect group-specific interactions or more general neighborhood spillovers. To address this, we re-estimate the analysis we conducted for immigrants, but this time with natives as the focal group. Estimates for the fully saturated model are presented in Table 8. Panel A provides a reminder of the baseline results for immigrants from Section 5, and Panel B provides analogous estimates for natives.[18] Column 1 shows that the overall neighbor coefficient for natives is 0.066 (Panel B), virtually identical to the estimate for immigrants (Panel A). What differs is who drives the effect. For natives, the coefficient on native-neighbors is a statistically significant 0.045, while immigrant-neighbors also exert a smaller, but positive and statistically significant, influence. Columns 2 and 3 of Panel B show that, as with immigrants, this pattern of peer effects is mediated by mobility rather than stability. With the caveats mentioned in the previous section, the point estimates in Column 3 can be interpreted as indicating that for natives, 3.7% of job offers come from fellow-natives in their neighborhood, and an additional 1.5% come from immigrant-peers.

The contrast between the immigrants and natives is informative. Immigrants respond only to immigrant neighbors, with native neighbors playing no detectable role, whereas natives respond primarily to native neighbors and, to a lesser extent, to immigrant neighbors. This asymmetry could reflect differences in network reach, labor market integration, or discrimination in the referral process. It also suggests that neighborhood peer effects are stronger within groups, and don't reflect a general neighborhood spillover. To the extent that they exist, positive cross-group spillovers run from immigrants to natives, but not vice versa.

6.2. **Family ties.** Having established that peer effects operate within identity groups and largely through mobility, the next question is whether the relevant ties lie with neighbors from outside the home, or come from close family members. To gauge their relative importance, while aligning our measure with designs that aggregate all neighborhood residents, we broaden the network to include family members. Panel C of Table 8 re-estimates the fully saturated models with co-resident family members counted among peers.[19] The coefficients rise markedly. In the full sample, overall peer effects nearly triple, and for immigrant-peers, the coefficient roughly quadruples. Among switchers, it rises from roughly 0.017 to 0.044. This suggests that strong-tie connections play an influential role in information transmission and/or referrals

These patterns indicate that designs aggregating close family members into peer networks may be bundling a larger within-household component with a smaller extra-household neighborhood component; our baseline isolates the latter. Panel C also helps explain why our baseline estimates are smaller than those in work that counts all co-residents (e.g., Schmutte): including family brings our coefficients much closer to those benchmarks in the full sample, though a gap remains among switchers.[20]

6.3. **Heterogeneous responses.** The third exercise asks whether responses to peer quality vary with the focal immigrant's characteristics. Figure 6 plots interaction coefficients from separate regressions

[18] Also analogous to Tables 4 and 5 for immigrants, Appendix Tables B6 and B7 provide supportive evidence for the plausible exogeneity of sorting within locales for natives. Appendix Tables B8 and B9 furnish estimates for the full range of specifications.

[19] Appendix Tables B10 and B11 furnish estimates for the full range of specifications.

[20] This likely reflects a combination of factors including our longer, more recent Canadian panel and immigrant-focused sample, as well as our switcher definition.

Average firm pay premium	Full (1)	Staying (2)	Switchers (3)
	Panel A: immigrant sample		
All peers	0.066***		
	(0.009)		
Immigrant peers	0.034***	0.007	0.017**
	(0.006)	(0.006)	(0.007)
Native peers	0.008	-0.002	0.010
	(0.005)	(0.007)	(0.008)
	Panel B: native sample		
All peers	0.066***		
	(0.010)		
Immigrant peers	0.010**	0.005	0.015***
	(0.004)	(0.005)	(0.005)
Native peers	0.045***	0.002	0.037***
	(0.007)	(0.007)	(0.007)
	Panel C: immigrant sample with family peers		
All peers	0.179***		
	(0.010)		
Immigrant peers	0.127***	0.007	0.044***
	(0.007)	(0.006)	(0.008)
Native peers	0.015***	-0.002	0.001
	(0.005)	(0.007)	(0.009)

TABLE 8. Natives and Family members *Notes.* This table presents estimates from the fully saturated model. Column 1 reports results for the full sample, where the dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Column also 2 reports results for the full sample, but with the dependent variable defined as an indicator for retention at the same employer in $t+1$. Column 3 reports results for the subsample of observations that directly follow a job switch, where the dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. In Panel A we report our benchmark results for the immigrant sample, which correspond to Columns 5 of Tables 6 and 7. Panel B reports the corresponding results for the native sample. Panel C reports results for the immigrant sample, where we include household members among peers. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

(marked by vertical dashed lines) that allow effects to differ by the focal immigrant's sex, age, education, the presence of children, and admission category.[21]

Two qualitative patterns stand out. First, the immigrant-peer channel is pervasive but not uniform. Both women and men benefit from immigrant-peer quality while women, unlike men, also display positive native-peer effects. Similarly, both younger (below age 34 in 2001) and older immigrants benefit from immigrant-peers, but only the older group also shows gains from native-peers. Second, the strength of the immigrant-peer effect varies with initial endowments. It is nearly twice as large for immigrants with lower schooling (fewer than 15 years at arrival) than for those with higher education, consistent with networks substituting for weaker access to formal hiring channels; conversely, the

[21] See Appendix Table B12 for details.

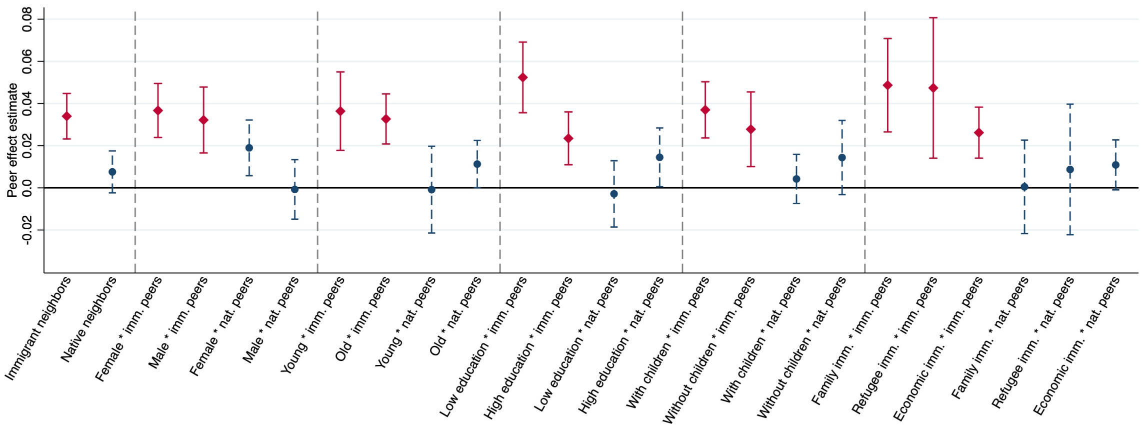


FIGURE 6. Heterogeneous responses *Notes.* Each set of plots in this figure shows peer effect coefficient estimates for the fully saturated model, along with their 95% confidence intervals. Estimates for different regressions are separated by a dashed line. The first two sets of estimates graphically depict point estimates from Column of Panel A and B, respectively in Table 6. The remaining sets report effects by sex, age, education at arrival, the presence of children in the household in 2001, and admission category. See appendix Table B12.

highly educated also benefit from native-peers, whereas the less educated do not. Peer effects are similar with and without children in the household, suggesting limited differentiation along this margin. By admission category, immigrant-peer effects are larger for family and refugee immigrants than for economic immigrants; the latter, however, also gain from native-peer quality. Taken together, these results are consistent with immigrant networks playing a bigger role where formal search and screening mechanisms are weaker or less accessible, with selected cross-group benefits from native-peers emerging for groups closer to mainstream labor-market channels.

Among switchers (Appendix Table B13), the contrasts are sharper. Positive immigrant-peer effects are concentrated among women (not men), among older (not younger) immigrants, and among those with lower education (not higher), in line with the view that networks are especially useful for facilitating upward moves when formal channels are thinner. By parental status, immigrant-peers matter for switchers with children, while native-peers matter for those without children, suggesting that constraints and social contacts shape which ties are operative at the time of a move. Finally, within admission categories, both immigrant- and native-peers matter for family-class immigrants, whereas we find immigrant- but no native-peer effects in the other categories. Overall, the mobility results reinforce that immigrant networks are most consequential for groups facing higher search frictions, with selective cross-group spillovers via native-peers in cases where labor-market attachment is stronger.

6.4. **Gender and recency.** Finally, we extend the homophily analysis beyond nationality and language by splitting immigrant- and native-peers along two non-ethnic markers of identity: gender and recency of arrival.

Figure 7 presents coefficient estimates for peer groups disaggregated along these dimensions for the fully saturated model.[22] For gender, the pattern is asymmetric. Among men, only male immigrant

[22]See Appendix Table B3 for more detail.

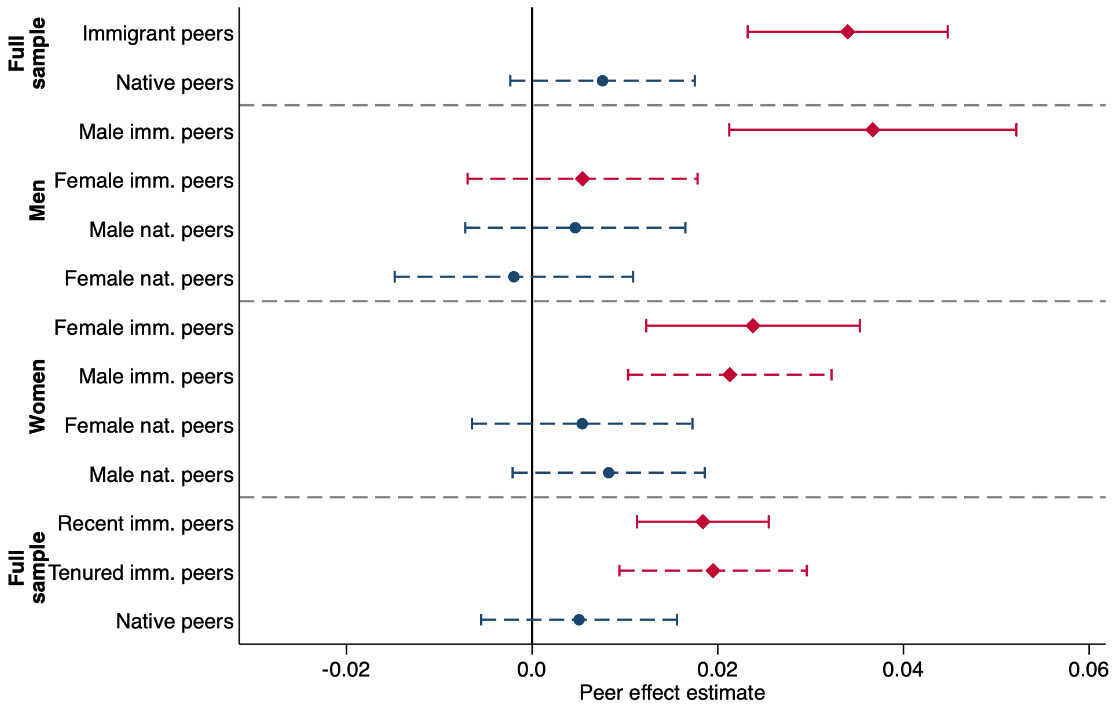


FIGURE 7. Homophily in neighborhood peer effects: Gender and Recency. *Notes.* Each set of plots in this figure shows peer effect coefficient estimates for the fully saturated model, along with their 95% confidence intervals. Estimates for different regressions are separated by a dashed line. The first two sets of estimates graphically depict point estimates from Column of Panel A and B, respectively in Table 6. The remaining sets are for immigrants and natives of the same sex vs. others; and recent vs. tenured immigrants. See appendix Table B3.

neighbors matter: coefficient on male immigrant-peers is a statistically significant 0.037, while the coefficient on female immigrant-peers is small and imprecisely estimated; native-peer coefficients are near zero. Among women, immigrant-peers of both genders matter in similar magnitude—with coefficients of just over 0.02—again with small and statistically insignificant native-peer coefficients. Thus, gendered homophily appears for men, whereas for women the immigrant-peer effect does not hinge on neighbor gender.

In terms of recency—defined as having arrived in the previous ten years—immigrant-peers who (like those in our analytic sample) arrived recently and those who are longer-settled have very similar effects, which are not statistically distinguishable. Native-peer coefficients remain small and insignificant. In sum, these results suggest that the immigrant-peer effect is gendered for men, but not for women; and that recency has no differential association.

7. ROBUSTNESS

In Table 9, we address several concerns that might call into question the robustness of our main results.[23] The fully saturated specification from Column 5 of Table 6 is repeated in the "Baseline" Column. First, we argued earlier that locale FEs absorb common shocks. However, this does not hold true if the shocks are time-varying. To address this, Column 1 adds locale-by-year fixed effects. The results are virtually unchanged.

	Firm pay premium						
	Baseline	Locale-Year FE	Country of birth-Year FE	At least 5 native and 5 immigrant peers	At least 10 native and 10 immigrant peers	At least 10 native and 10 immigrant peers; Never moved	Drop low population postal codes
Average firm pay premium	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant peers	0.034***	0.031***	0.034***	0.051***	0.051***	0.054**	0.034***
	(0.006)	(0.005)	(0.006)	(0.010)	(0.015)	(0.023)	(0.006)
Native peers	0.008	0.006	0.007	0.017**	0.028*	0.022	0.007
	(0.005)	(0.005)	(0.005)	(0.008)	(0.014)	(0.022)	(0.005)
Test: Immigrant peers = Native peers							
F	10.994	9.739	11.915	6.812	1.361	1.036	11.604
Prob > F	0.001	0.002	0.001	0.009	0.244	0.309	0.001
N.Obs.	900,000	900,000	900,000	700,000	400,000	100,000	900,000

TABLE 9. Robustness *Notes.* This table presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Column 1 presents estimates for our main specification, and corresponds to Column 5 in Table 6. In Columns 2 and 3 we include locale-by-year and country-by-year fixed effects, respectively. Columns 4-7 present estimates for subsets of the main sample, after we impose different restrictions. Individual controls and contextual effects are the same as in Table 6. p-values of the test for $\bar{\psi}^1_{jt-1} = \bar{\psi}^0_{jt-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Second, even with locale fixed effects, peer effects might pick up time-varying shocks specific to origin-country groups (on either the demand or supply side). Column 2 includes country-of-birth-by-year fixed effects to account for this. Again, the peer effect estimates are virtually unchanged.

Third, in neighborhoods with a small number of immigrant-peers, estimates may be attenuated because the network quality measure is noisy in very small cells. Column 3 restricts the sample to neighborhoods where immigrants in our core sample have *at least* five peers in both immigrant and native networks. This reduces the sample by roughly one fifth. Nevertheless, the results are qualitatively similar: peer effects are positive, of similar magnitude, and significantly larger for immigrant- than for native-peers. The same holds in Column 4, which imposes a 10-peer minimum.

Fourth, although Section 4 shows that neighborhood moves do not tend to precede job switches, there may still be concern that immigrants sort into neighborhoods closer to their workplaces. Such location sorting could bias upward the peer-effect estimates for neighborhood switchers (not to be confused with *job* switchers). This bias should not characterize individuals who remain in the same neighborhood throughout. Column 5 therefore adds the sample restriction that immigrants must

[23]A job switchers-only analogue to this table is in Appendix Table B14; the qualitative ordering mirrors the one in this section, although estimates are imprecise due to sample loss.

not have moved neighborhoods between 2001 and 2017, along with the 10-peer minimum. For the subsample of roughly 100,000 immigrants who meet these criteria, the results remain intact (if anything, slightly larger), suggesting that workplace-based location sorting is unlikely to drive our findings.[24]

Finally, Column 6 reports results for a subsample living in neighborhoods that are not *too small*: we drop neighborhoods in the bottom decile of total resident population, where peer interactions may be more scarce.[25] The results are again virtually identical.

	Firm pay premium		
	Baseline	World area of	World area of
Average firm		birth sample	birth sample
pay premium	(1)	(2)	(3)
Immigrant peers	0.034***	0.062***	
	(0.006)	(0.009)	
Native peers	0.008	0.003	0.005
	(0.005)	(0.005)	(0.005)
Same world area of birth			0.040***
			(0.004)
Different world area of birth			0.014***
			(0.005)
Test: Immigrant peers = Native peers			
F	10.994	31.684	
Prob > F	0.001	0.000	
Test: Same world area of birth = Different world area of birth			
F			15.949
Prob > F			0.000
Test: Same world area of birth = Native peers			
F			26.049
Prob > F			0.000
N.Obs.	700,000	700,000	700,000

TABLE 10. Peer networks by world area of birth *Notes.* This table presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Column 1 reports our estimate for the main sample, and corresponds to Column 5 in Table 6. Column 2 reports the same estimates on the subsample of immigrants who have at least one immigrant-peer from the same world area of birth and one from a different world area of birth. Column 3 presents our estimates when we disaggregate the immigrant-peer network by whether neighbors share the same world area of birth, on the same sample as Column 2. Individual controls and contextual effects are the same as in Table 6. p-values of the test for $\bar{\psi}^1_{j,t-1} = \bar{\psi}^0_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

In a final robustness check on the definition of origin, we replace shared country of birth with broader shared world areas: America and Oceania, Europe, Africa, West Asia, East Asia, South Asia, and South-East Asia (Table 10).[26] While continental geography is arguably a less salient marker of identity than nationality, this specification avoids the sample loss inherent in the country exercise: aggregating to world areas retains essentially the full immigrant sample even under the minimum-peer thresholds.

[24]We note that never-movers are a selected subset, so this is a conservative check on sorting rather than a new source of identification.

[25]Note that dropped neighborhoods do not differ materially on observables from those retained.

[26]We present analogous estimates for the job switchers sample in Appendix Table B15.

It also expands peer sets, yielding a more precisely measured peer-quality regressor and reducing attenuation from small cells. The resulting coefficients are larger—over twice the size of the country-group estimates—which we interpret as a mechanical consequence of improved measurement and reweighting toward denser networks, rather than a stronger underlying channel. The qualitative inference is unchanged: effects run through immigrant-peers, not native-peers.

8. Conclusion

This paper has examined whether residential peers shape immigrants' employment in high-paying firms, and whether peer effects depend on shared identity. Using linked Canadian employer-employee data combined with immigration records, we find that peer effects matter for immigrants' employer quality: immigrants whose neighborhood peers work for firms that pay higher premiums tend to work at higher pay-premium firms themselves. These effects are concentrated among job switchers, consistent with a mobility margin, and they are driven by immigrant- rather than native-peers. Within immigrant networks, peer effects are stronger when neighbors share a country of birth or mother tongue, underscoring the potential for homophily to shape economic integration.

These results suggest that residential networks matter, but in circumscribed ways. That peers' employer quality improves employer quality among job switchers but does not improve their probability of staying in a job suggests that peers may influence employer mobility rather than job stability. Our deliberate exclusion of co-residing household members yields smaller coefficients than designs that pool them with other neighbors, but this isolates the extra-household margin of peer exposure and highlights its independent contribution. That immigrant-peers matter more than native-peers, and that shared identity amplifies these associations, suggests that immigrant networks may substitute for thinner formal ties to the labor market and that information transmitted through familiar channels may be more salient and credible.

From a policy perspective, the findings speak to both the promise and the limits of neighborhood networks in immigrant integration. They suggest that proximity to well-placed peers can improve access to better employers, and primarily when identity is shared. Policies that disperse immigrants widely may therefore weaken these peer effects without necessarily creating alternative pathways into high-paying firms. At the same time, our findings highlight that networks alone cannot close immigrant–native gaps in employer access; complementary measures that strengthen immigrants' connections to mainstream labor market institutions remain essential.

These conclusions should be interpreted with caution. The evidence comes from large Canadian metropolitan areas, where immigrant populations are dense, multi-ethnic, and long viewed as an asset rather than a liability. Peer dynamics may play out differently in contexts where immigrants are fewer, more isolated, or politically contested. Moreover, our estimates capture reduced-form exposure effects rather than specific mechanisms of job transmission. Still, the results underline that local, identity-based networks continue to shape how immigrants navigate the job market, even in settings with diverse and open labor markets.

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APPENDIX A. ADDITIONAL FIGURES

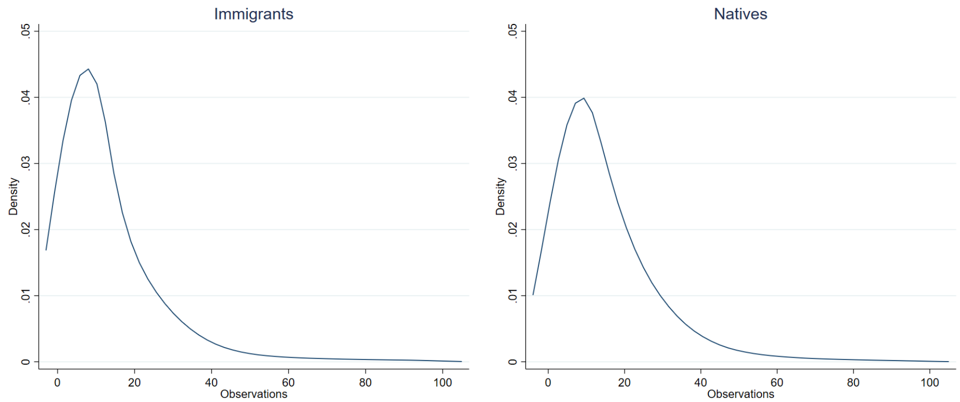

FIGURE A1. Distribution of neighborhood size by immigrant and native networks. *Notes.* The figures show the distribution of neighborhood size for immigrants in the analytic sample, by neighbors' immigrant status.

APPENDIX B. ADDITIONAL TABLES

	Firm pay premium		
Average firm pay premium	Baseline (1)	0-year lag (2)	2-years lag (3)
	Panel A: all peers		
All peers	0.066***	0.067***	0.061***
	(0.009)	(0.009)	(0.009)
N.Obs.	900,000	1,000,000	800,000
	Panel B: immigrants and native peers		
Immigrant peers	0.034***	0.036***	0.033***
	(0.006)	(0.006)	(0.006)
Native peers	0.007	0.008*	0.005
	(0.005)	(0.005)	(0.005)
Test: Immigrant peers = Native peers			
F	10.994	11.769	12.324
Prob > F	0.001	0.001	0.001
N.Obs.	900,000	1,000,000	800,000

TABLE B1. Peer effect on immigrants: different lags *Notes.* Panel A presents coefficient estimates for ϕ in model 2, while Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. Each Column presents estimates for variations of our main models, where we vary the lag with which we construct immigrants' peer network. Column 1 presents estimates for the main sample, where the peer network is constructed with a 1-year lag, and corresponds to Column 5 in table 6. Columns 2 and 3 present alternative estimates where the peer network is constructed with 0-year and 2-years lags, respectively. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls and contextual effects are the same as in Panel B of Table 6. p-values of the test for $\overline{\psi^1}_{j,t-1} = \overline{\psi^0}_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

	Firm pay premium			
Average firm pay premium	Baseline (1)	Montréal (2)	Toronto (3)	Vancouver (4)
		Panel A: all peers		
All peers	0.066***	0.030	0.064***	0.064***
	(0.009)	(0.019)	(0.012)	(0.018)
N.Obs.	900,000	100,000	600,000	200,000
		Panel B: immigrants and native peers		
Immigrant peers	0.034***	0.018*	0.032***	0.039***
	(0.006)	(0.010)	(0.008)	(0.011)
Native peers	0.008	0.001	0.006	0.003
	(0.005)	(0.014)	(0.006)	(0.012)
Test: Immigrant peers = Native peers				
F	10.994	0.853	6.772	4.078
Prob > F	0.001	0.357	0.010	0.046
N.Obs.	900,000	100,000	600,000	200,000

TABLE B2. Peer effect on immigrants by CMA *Notes.* Panel A presents coefficient estimates for ϕ in model 2, while Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Column 1 presents estimates for the main sample, which includes immigrants residing in the Montréal, Toronto and Vancouver CMAs, and corresponds to Column 5 in table 6. Columns 2, 3, and 4 present estimates for the subsample of individuals residing in each CMA, separately. Individual controls and contextual effects are the same as in Panel B of Table 6. p-values of the test for $\overline{\psi^1}_{j,t-1} = \overline{\psi^0}_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

	Firm pay premium					
Average firm pay premium	Baseline (1)	Top 10 countries of birth (2)	Top 10s mother tongues (3)	Men (4)	Women (5)	All (6)
Immigrant peers	0.034***					
	(0.006)					
Native peers	0.008	-0.005	0.001			0.005
	(0.005)	(0.007)	(0.007)			(0.005)
Same country of birth		0.046***				
		(0.006)				
Different country of birth		0.024***				
		(0.007)				
Same mother tongue			0.038***			
			(0.005)			
Different mother tongue			0.016***			
			(0.006)			
Female immigrant peers				0.005		
				(0.006)		
Male immigrant peers				0.037***		
				(0.008)		
Female native peers				-0.002		
				(0.007)		
Male native peers				0.005		
				(0.006)		
Female immigrant peers					0.024***	
					(0.006)	
Male immigrant peers					0.021***	
					(0.006)	
Female native peers					0.005	
					(0.006)	
Male native peers					0.008	
					(0.005)	
Tenured immigrant peers						0.012***
						(0.005)
Recent immigrant peers						0.018***
						(0.004)
N.Obs.	900,000	400,000	400,000	500,000	300,000	800,000

TABLE B3. Homophily *Notes.* Column 1 presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. The other Columns present coefficient estimates for variations of model 3 for the immigrant sample, where we disaggregate the peer network along different dimensions. In Columns 2 and 3, we split immigrant-peers by country of birth and mother tongue, respectively. In Columns 4 and 5, we split immigrant- and native-peers by gender. In Column 6, we split immigrant-peers by tenure in Canada. Tenured immigrants have lived for more than 10 years in the country. In each Column, the sample is restricted to immigrants who have at least one neighbor in each subgroup in which we disaggregate the peer network. Individual controls and contextual effects are the same as in Panel B of Table 6. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

	Firm pay premium					
	Baseline	Top 10 countries of birth	Top 10s mother tongues	Men	Women	All
Average firm pay premium	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant peers	0.017**					
	(0.007)					
Native peers	0.010	-0.010	0.005			0.011
	(0.008)	(0.014)	(0.014)			(0.011)
Same country of birth		0.025***				
		(0.008)				
Different country of birth		0.016				
		(0.011)				
Same mother tongue			0.018***			
			(0.006)			
Different mother tongue			0.010			
			(0.010)			
Female immigrant peers				0.010		
				(0.009)		
Male immigrant peers				0.010		
				(0.008)		
Female native peers				0.012		
				(0.012)		
Male native peers				0.006		
				(0.008)		
Female immigrant peers					0.020**	
					(0.009)	
Male immigrant peers					0.006	
					(0.010)	
Female native peers					-0.009	
					(0.012)	
Male native peers					0.011	
					(0.010)	
Tenured immigrant peers						0.009
						(0.008)
Recent immigrant peers						0.022***
						(0.008)
N.Obs.	100,000	60,000	60,000	70,000	40,000	100,000

TABLE B4. Homophily: switchers sample *Notes.* Column 1 presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. The other Columns present coefficient estimates for variations of model 3 for the immigrant sample, where we disaggregate the peer network along different dimensions. In Columns 2 and 3, we split immigrant-peers by country of birth and mother tongue, respectively. In Columns 4 and 5, we split immigrant- and native-peers by gender. In Column 6, we split immigrant-peers by tenure in Canada. Tenured immigrants have lived for more than 10 years in the country. In each Column, the sample is restricted to immigrants who have at least one neighbor in each subgroup in which we disaggregate the peer network. Individual controls and contextual effects are the same as in Panel B of Table 7. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

		Retention	
	Baseline	High initial firm pay premium	Low initial firm pay premium
Average firm pay premium	(1)	(2)	(3)
Immigrant peers	0.007	-0.001	0.006
	(0.006)	(0.008)	(0.009)
Native peers	-0.002	-0.005	-0.003
	(0.007)	(0.009)	(0.010)
N.Obs.	800,000	400,000	400,000

TABLE B5. Retention by initial firm FE *Notes.* The table presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is an indicator for retention at the same employer in $t + 1$. Column 1 presents estimates for the main sample, and corresponds to Column 5 in table 7. Columns 2 and 3 present the estimates when we split the sample by whether the firm FE preceding the job switch was above or below the median. Individual controls and contextual effects are the same as in Panel B of Table 6. p-values of the test for $\overline{\psi^1}_{j,t-1} = \overline{\psi^0}_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

	Native sample			
	(1)	(2)	(3)	(4)
Female	0.426	0.001	0.001	0.001
Age	0.940	0.011	0.010	0.008
Married	0.545	0.024	0.024	0.022
Residuals from Eq. 1	0.000	0.000	0.000	0.000
Locale FE	No	Yes	Yes	No
Year FE	No	No	Yes	No
Locale-Year FE	No	No	No	Yes

TABLE B6. Sorting within locales: natives *Notes.* This table presents the R^2 for a set of regressions with a characteristic for a randomly selected individual on the left-hand side, and the average of that variable for all other residents in the same neighborhood on the right-hand side. We run separate regressions for the following individual characteristics: female, age, married, and residuals from model 1. Column 1 presents the R^2 for univariate regressions, where we only include the average characteristic among neighbors on the right-hand side. We include locale fixed effects in Column 2, add year fixed effects in Column 2, and a locale by year fixed effect in Column 3.

	Native-peer sample			
	(1)	(2)	(3)	(4)
Agriculture, forestry, fishing, hunting	0.001	0.001	0.001	0.001
Mining, utilities, construction	0.008	0.000	0.000	0.000
Manufacturing	0.030	0.000	0.000	0.000
Wholesale and retail trade, transportation	0.064	0.000	0.000	0.000
Information, finance, insurance, etc.*	0.177	0.001	0.000	0.000
Education, healthcare, social assistance	0.049	0.001	0.000	0.000
Arts, entertainment, hospitality	0.003	0.000	0.000	0.000
Other services	0.003	0.000	0.000	0.000
Firm size	0.055	0.000	0.000	0.000
Commuting distance	0.055	0.000	0.000	0.000
Locale FE	No	Yes	Yes	No
Year FE	No	No	Yes	No
Locale-Year FE	No	No	No	Yes

TABLE B7. Sorting within locales: native movers *Notes.* This table presents the R^2 for a set of regressions with a characteristic for a randomly selected individual among the subset of job switchers who change residential neighborhood in the year following the job switch on the left-hand side, and the current average of that variable for their future neighbors on the right-hand side. We run separate regressions for the following characteristics: industry, firm size and commuting distance. Column 1 presents the R^2 for univariate regressions, where we only include the average characteristic among future neighbors on the right-hand side. We include locale fixed effects in Column 2, add year fixed effects in Column 2, and a locale by year fixed effect in Column 3.

* Information, finance, insurance, real estate, professional, scientific and technical services, management of companies, administrative services

Average firm pay premium	*Firm pay premium* (1)	(2)	(3)	(4)	(5)
	Panel A: all peers				
All peers	0.317***	0.265***	0.130***	0.099***	0.066***
	(0.026)	(0.023)	(0.011)	(0.011)	(0.010)
N.Obs.	1,400,000	1,400,000	1,400,000	1,400,000	1,400,000
	Panel B: immigrants and native peers				
Immigrant peers	0.078***	0.061***	0.031***	0.020***	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Native peers	0.202***	0.174***	0.078***	0.062***	0.045***
	(0.021)	(0.018)	(0.008)	(0.008)	(0.007)
Test: Immigrant peers = Native peers					
F	36.261	39.447	29.830	24.586	21.497
Prob > F	0.000	0.000	0.000	0.000	0.000
N.Obs.	1,400,000	1,400,000	1,400,000	1,400,000	1,400,000
Year FE	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Locale FE	No	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes	Yes
Previous employer firm pay premium	No	No	No	No	Yes

TABLE B8. Peer effect on natives *Notes.* Panel A presents coefficient estimates for ϕ in model 2, while Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the native sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls include quadratic age, sex, and marital status. Contextual effects include the average age and average square of age among the individual's neighborhood peers, the share of women, the share of peers by marital status, and the average individual fixed effects from model 1 among the individual's peers. In panel B, contextual effects also include average years of education, share by official language knowledge at arrival, share by immigration category, and share by country of birth, among immigrant-peers. p-values of the test for $\overline{\psi^1}_{j,t-1} = \overline{\psi^0}_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Average firm pay premium	(1)	(2)	(3)	(4)	(5)
	Panel A: probability of staying in job				
Immigrant peers	-0.008	-0.015***	-0.004	0.003	0.005
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Native peers	-0.006	-0.017**	-0.009	-0.000	0.002
	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)
	Panel B: firm pay premium for job switchers				
Immigrant peers	0.071***	0.053***	0.033***	0.026***	0.015***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Native peers	0.182***	0.148***	0.071***	0.057***	0.037***
	(0.019)	(0.016)	(0.009)	(0.009)	(0.007)
Test: Immigrant peers = Native peers					
F	33.106	32.961	11.331	7.856	7.181
Prob > F	0.000	0.000	0.001	0.005	0.008
Year FE	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Locale FE	No	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes	Yes
Previous employer firm pay premium	No	No	No	No	Yes

TABLE B9. Stayers and switchers: natives *Notes.* Panel A presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the native sample. The dependent variable is an indicator for retention at the same employer in $t+1$. Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the native sample, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls and contextual effects are the same as in Panel B of Table B8. p-values of the test for $\bar{\psi}^1_{j,t-1} = \bar{\psi}^0_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Average firm pay premium	*Firm pay premium* (1)	(2)	(3)	(4)	(5)
	Panel A: all peers				
All peers	0.392***	0.286***	0.222***	0.214***	0.179***
	(0.013)	(0.011)	(0.010)	(0.011)	(0.010)
N.Obs.	900,000	900,000	900,000	900,000	900,000
	Panel B: immigrants and native peers				
Immigrant peers	0.234***	0.185***	0.154***	0.150***	0.127***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
Native peers	0.079***	0.048***	0.022***	0.018***	0.015***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)
Test: Immigrant peers = Native peers					
F	142.505	155.590	166.050	166.890	148.612
Prob > F	0.000	0.000	0.000	0.000	0.000
N.Obs.	900,000	900,000	900,000	900,000	900,000
Year FE	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Locale FE	No	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes	Yes
Previous employer firm pay premium	No	No	No	No	Yes

TABLE B10. Peer effect on immigrants: including family peers *Notes.* This table presents peer effect estimates for the immigrant sample, when we include family members among neighborhood peers. Panel A presents coefficient estimates for ϕ in model 2, while Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls and contextual effects are the same as in Table 6. p-values of the test for $\overline{\psi^1}_{j,t-1} = \overline{\psi^0}_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Average firm pay premium	(1)	(2)	(3)	(4)	(5)
	Panel A: probability of staying in job				
Average ψ: immigrant peers	-0.015**	-0.010	-0.001	0.004	0.007
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Average ψ: native peers	0.000	-0.008	-0.007	-0.003	-0.002
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
	Panel B: firm pay premium for job switchers				
Average ψ: immigrant peers	0.149***	0.110***	0.081***	0.075***	0.044***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.008)
Average ψ: native peers	0.082***	0.049***	0.021**	0.016	0.001
	(0.013)	(0.011)	(0.011)	(0.010)	(0.009)
Test: Immigrant peers = Native peers					
F	13.620	14.056	14.261	13.667	6.557
Prob > F	0.000	0.000	0.000	0.000	0.011
Year FE	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Locale FE	No	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes	Yes
Previous employer firm pay premium	No	No	No	No	Yes

TABLE B11. Stayers and switchers: including family peers *Notes.* Panel A presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample, including family peers in the neighborhood network. The dependent variable is an indicator for retention at the same employer in $t + 1$. Panel B presents estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample including family peers in the immigrant neighborhood network, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Individual controls and contextual effects are the same as in Panel B of Table 6. p-values of the test for $\bar{\psi}^1_{j,t-1} = \bar{\psi}^0_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Average firm pay premium	*Firm pay premium* (1)	(2)	(3)	(4)	(5)	(5)
Immigrant peers	0.034***					
	(0.006)					
Native peers	0.008					
	(0.005)					
Female * Immigrant peers		0.037***				
		(0.007)				
Male * Immigrant peers		0.032***				
		(0.008)				
Female * Native peers		0.019***				
		(0.007)				
Male * Native peers		-0.001				
		(0.007)				
Young * Immigrant peers			0.036***			
			(0.001)			
Old * Immigrant peers			0.033***			
			(0.006)			
Young * Native peers			-0.001			
			(0.011)			
Old * Native peers			0.011**			
			(0.006)			
Low education * Immigrant peers				0.052***		
				(0.009)		
High education * Immigrant peers				0.024***		
				(0.006)		
Low education * Native peers				-0.003		
				(0.008)		
High education * Native peers				0.015**		
				(0.007)		
With children * Immigrant peers					0.037***	
					(0.007)	
Without children * Immigrant peers					0.028***	
					(0.009)	
With children * Native peers					0.004	
					(0.006)	
Without children * Native peers					0.014	
					(0.009)	
Economic immigrants * Immigrant peers						0.026***
						(0.006)
Family immigrants * Immigrant peers						0.049***
						(0.011)
Refugee immigrants * Immigrant peers						0.047***
						(0.017)
Other immigrants * Immigrant peers						0.109**
						(0.051)
Economic immigrants * Native peers						0.011*
						(0.006)
Family immigrants * Native peers						0.001
						(0.011)
Refugee immigrants * Native peers						0.009
						(0.016)
Other immigrants * Native peers						-0.088**
						(0.040)
N.Obs.	900,000	900,000	900,000	900,000	900,000	900,000

TABLE B12. Heterogeneity *Notes.* Column 1 presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. The other Columns present coefficient estimates for model 3 for the immigrant sample, where we split the main sample into subgroups. In Columns 2 and 3, we split immigrants by sex and age, respectively. In Columns 4 we split the sample by educational attainment at arrival and in Column 5 by parental status. In Column 6, we split immigrant-peers by immigration category. Individual controls and contextual effects are the same as in Panel B of Table 6. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

Average firm			*Firm pay premium*			
pay premium	(1)	(2)	(3)	(4)	(5)	(5)
Immigrant peers	0.017**					
	(0.007)					
Native peers	0.010					
	(0.008)					
Female * Immigrant peers		0.027**				
		(0.011)				
Male * Immigrant peers		0.011				
		(0.009)				
Female * Native peers		0.010				
		(0.011)				
Male * Native peers		0.011				
		(0.010)				
Young * Immigrant peers			0.017			
			(0.011)			
Old * Immigrant peers			0.017**			
			(0.009)			
Young * Native peers			0.018			
			(0.015)			
Old * Native peers			0.006			
			(0.009)			
Low education * Immigrant peers				0.029**		
				(0.012)		
High education * Immigrant peers				0.011		
				(0.009)		
Low education * Native peers				0.001		
				(0.012)		
High education * Native peers				0.014		
				(0.011)		
With children * Immigrant peers					0.019**	
					(0.009)	
Without children * Immigrant peers					0.012	
					(0.011)	
With children * Native peers					-0.002	
					(0.010)	
Without children * Native peers					0.035***	
					(0.012)	
Economic immigrants * Immigrant peers						0.014
						(0.008)
Family immigrants * Immigrant peers						0.025*
						(0.014)
Refugee immigrants * Immigrant peers						0.025
						(0.024)
Other immigrants * Immigrant peers						0.037
						(0.112)
Economic immigrants * Native peers						0.008
						(0.010)
Family immigrants * Native peers						0.027*
						(0.016)
Refugee immigrants * Native peers						-0.013
						(0.028)
Other immigrants * Native peers						0.012
						(0.090)
N.Obs.	100,000	100,000	100,000	100,000	100,000	100,000

TABLE B13. Heterogeneity: switchers sample *Notes.* Column 1 presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. The other Columns present coefficient estimates for model 3 for the immigrant sample, where we split the main sample into subgroups. In Columns 2 and 3, we split immigrants by sex and age, respectively. In Columns 4 we split the sample by educational attainment at arrival and in Column 5 by parental status. In Column 6, we split immigrant-peers by immigration category. Individual controls and contextual effects are the same as in Panel B of Table 6. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

	Firm pay premium						
	Baseline	Locale-Year FE	Country of birth-Year FE	At least 5 native and 5 immigrant peers	At least 10 native and 10 immigrant peers	At least 10 native and 10 immigrant peers; Never moved	Drop low population postal codes
Average firm pay premium	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant peers	0.017**	0.012	0.015**	0.023*	0.037*	0.062*	0.017**
	(0.007)	(0.007)	(0.007)	(0.013)	(0.020)	(0.035)	(0.007)
Native peers	0.010	0.007	0.010	0.022*	0.029	0.073**	0.010
	(0.008)	(0.009)	(0.008)	(0.012)	(0.020)	(0.028)	(0.008)
Test: Immigrant peers = Average ψ native peers							
F	0.300	0.131	0.204	0.005	0.076	0.058	0.327
Prob > F	0.584	0.718	0.651	0.946	0.783	0.810	0.568
N.Obs.	100,000	100,000	100,000	90,000	60,000	20,000	100,000

TABLE B14. Robustness: switchers sample *Notes.* This table presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Column 1 presents estimates for our main specification, and corresponds to Column 5 in Table 7. In Columns 2 and 3 we include locale-by-year and country-by-year fixed effects, respectively. Columns 4-7 present estimates for subsets of the main sample, after we impose different restrictions. Individual controls and contextual effects are the same as in Table 7. p-values of the test for $\bar{\psi}^1_{jt-1} = \bar{\psi}^0_{jt-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.

	Firm pay premium		
	Baseline	World area of	World area of
Average firm		birth sample	birth sample
pay premium	(1)	(2)	(3)
Immigrant peers	0.017**	0.028***	
	(0.007)	(0.011)	
Native peers	0.010	-0.004	-0.003
	(0.008)	(0.010)	(0.010)
Same world area of birth			0.017***
			(0.006)
Different world area of birth			0.006
			(0.008)
Test: Immigrant peers = Native peers			
F	0.300	3.960	
Prob > F	0.584	0.047	
Test: Same world area of birth = Different world area of birth			
F			1.290
Prob > F			0.257
Test: Same world area of birth =Native peers			
F			2.878
Prob > F			0.091
N.Obs.	100,000	100,000	100,000

TABLE B15. Peer networks by world area of birth: switchers sample *Notes.* This table presents coefficient estimates for ϕ_0 and ϕ_1 in model 3 for the immigrant sample, for the subsample of observations that directly follow a job switch. The dependent variable is the firm pay premium estimate $\psi_{j(i,t)}$ from model 1. Column 1 reports our estimate for the main sample, and corresponds to Column 5 in Table 7. Column 2 reports the same estimates on the subsample of immigrants who have at least one immigrant-peer from the same world area of birth and one from a different world area of birth. Column 3 presents our estimates when we disaggregate the immigrant-peer network by whether neighbors share the same world area of birth, on the same sample as Column 2. Individual controls and contextual effects are the same as in Table 7. p-values of the test for $\bar{\psi}^1_{j,t-1} = \bar{\psi}^0_{j,t-1}$ are presented in the bottom row. Robust standard errors in parentheses are clustered at the locale level. *** p<0.01, ** p<0.05, * p<0.1.