DISCUSSION PAPER SERIES

IZA DP No. 9942

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May 2016

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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May 2016

ABSTRACT

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In this paper we highlight a specific mechanism through which social networks help in job search. We characterize the strength of a network by its likelihood of providing a job offer. Using a theoretical model we show that the wage differential in jobs found using networks versus those found using formal channels, decreases as the network becomes stronger. We verify this result for recent immigrants to Canada for whom a strong network is captured by the presence of a 'close tie.' Furthermore, structural estimates confirm that the presence of a close tie operates by increasing the likelihood of generating a job offer from the network rather than by altering the wage distribution from which an offer is drawn.

JEL Classification: J3

Keywords: job search, migration, networks

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* We thank the Canadian Labour Market and Skills Researcher Network for funding this research. We also thank its reviewers, David Dorn and participants at the CLSRN conference, Growth and Development conference at ISI Delhi, the NBER Summer Institute and at seminars and workshops at CEMFI, Collegio Carlo Alberto, EIEF, the IZA, the London School of Economics, Northeastern, Singapore Management University, SOLE, Universitat Autonoma de Barcelona, Universitat Pompeu Fabra, University College London and the University of New South Wales for helpful comments. We are grateful to Miles Corak for enabling access to the data housed in Statistics Canada, Ottawa, Canada. The views expressed herein are those of the authors and do not necessarily reflect the views of the Canadian Labour Market and Skills Researcher Network or of Statistics Canada.

1 Introduction

Social networks have long been viewed as reservoirs of information that help match job seekers with vacancies (Ioannides and Loury 2004; Calvo-Armengol and Jackson 2004, 2007).[1] In a review of literature spanning the last three decades, covering the United States and other countries, Topa (2011) notes that at least half of all jobs are typically found through informal contacts. While the importance of networks in job search has been firmly established, not much is known about the channels through which they operate. We show that in the case of very recent immigrants to Canada, effective networks operate by providing a greater number of job offers rather than by altering the type of offers.

Drawing on Montgomery (1992), we model the effect of increasing the likelihood of receiving a job offer from the network. We derive the counter-intuitive implication that observed difference in wages in jobs found using networks versus those found using formal channels decreases as network strength, defined as the probability of generating a job offer, increases. Put differently, the network wage premium decreases with network strength. That this result holds even when we allow the network and formal wage offer distributions to differ from each other, and that it holds not just at the mean but also at most percentiles, are novel contributions of this paper.

We test the predictive value of our model for a nationally representative survey of recent immigrants to Canada. In the data, a strong network is captured using the presence of at least one 'close tie' (relative or friend) in Canada at the time of entry. Employing a difference-in-differences approach we confirm our model's implications. Finally, as an additional check, we estimate a structural model to uncover the underlying network and formal wage-offer distributions and offer probabilities. The parameter estimates confirm that the presence of a close tie operates by increasing the likelihood of generating an offer from the network rather than by altering the

[1] Other roles of social networks have included acting as collateral in credit markets (Karlan et al 2009), providing insurance against income shocks (Ambrus et al 2014; Kinnan and Townsend 2012; Munshi and Rosenzweig 2016), and overcoming moral hazard (Dhillon et al 2014; Jackson and Schneider 2011).

distribution from which this offer is drawn.

Although the situation of recent immigrants to Canada is unlikely to be unique, we make no claim that all networks work in the manner that we describe. Our setting may differ because newly arrived immigrants to Canada, although generally well-educated, may be impatient to find some employment quickly. Networks may play a quite different role for more established immigrants or for natives. Moreover, we are agnostic about whether networks provide better (or worse) offers. The empirical literature is divided on this point, perhaps because the type of jobs networks provide depends on the specifics of the network. Some studies have found that networks help overcome adverse selection or improve match productivity leading to higher starting wages for workers hired using referrals (Brown et al 2016; Damm 2009; Dustmann et al 2015; Hensvik and Skans 2016; Schmutte 2015a). On the other hand Aslund and Skans (2010) and Bentolila et al (2010) find a wage penalty associated with the use of networks. In another set of papers, whether the use of networks results in a penalty or a premium is ambiguous: in Beamen 2012, it depends on the vintage of the network, while in Pellizzari 2010, it depends on the efficiency of the formal channels.

A few other papers have examined the mechanisms through which networks operate. In Dustmann et al 2015, a referred worker's firm-specific productivity is less uncertain than that of a worker hired through formal (impersonal) channels. Consequently, referred workers earn higher wages and are less likely to leave the firm. The authors find support for this hypothesis using matched employer-employee data from Germany. Schmutte (2015b) develops a model in which the intensity with which referrals are used is endogenously determined and exhibits a non-monotonic relationship with labor market tightness. Additionally, whether referrals get converted to jobs is inversely related to the intensity of use of referrals. He verifies this last prediction using data from the United States.[2] We add to this growing body of literature.

[2]Some other recent papers that combine theory with empirical evidence to study how networks operate in the labor market include Beaman and Magruder (2012), Hensvik and Skans (2016) and Schmutte (2015a).

The empirical literature has measured networks in different ways. Some papers emphasize the spatial dimension of networks (Hellerstein et al. 2011; Hellerstein et al. 2014). Topa and Zenou (2015) define networks using a common social space based on race, ethnicity, age, nationality, tastes and other attributes, and recognize that there may be an overlap between physical and social space. Others focus on the workplace and use co-workers to define a network (Cingano and Rosolia 2012; Glitz 2015; Weber et al 2014). In developing countries networks have been characterized using community based ties, for example, Munshi (2011) defines networks in India along caste lines. Immigrant networks have traditionally been defined along ethnic or country of origin dimensions (Borjas 2000; Patacchini and Zenou 2012; Patel and Vella 2013).

Granovetter (1973) and later Boorman (1975) distinguish between strong and weak social ties. The former consist of family members and close friends, and the latter of acquaintances or friends of friends. Recent papers that have looked at the different effects of these two types of ties obtain mixed results. Kuzubas and Szabo (2015) study unemployed workers in Indonesia and find that workers are more likely to search through their strong ties when the ethnic network is either very small or very large. They also show that workers who find their job using strong ties earn less than others due to lower match quality. Using Swedish data on young labor market entrants, Kramarz and Skans (2014) find an important role for strong ties captured using parental networks. Young workers appear to benefit from shorter transitions into the first jobs and better labor market outcomes after a few years into the job. Giulietti et al (2014) look at rural to urban migration in China and find that strong and weak ties act as complements in influencing the decision to migrate. Keeping this rich literature in mind, in Goel and Lang (2009), we tested the empirical validity of two different measures of network strength: a) the traditional (weak ties) measure consisting of persons from the immigrant's country of origin living in his locality, and b) the presence of close ties captured by at least one relative or friend in Canada at the time of entry. We find that the former does not satisfy basic conditions (discussed in section 3) to be a valid proxy for network strength, while the close ties measure does. In this paper, we therefore use close ties to capture network strength.

The paper is organized as follows. In section 2 we develop the theoretical model and derive its implication. Section 3 describes our empirical framework, section 4 provides a brief description of the data, section 5 presents the empirical results and section 6 contains the structural estimations. We conclude in section 7.

2 Theoretical Model

Our model draws on Montgomery (1992). He considers a worker who receives job offers from two sources to which we will refer as 'the worker's network' and 'formal channels.' In that paper the two sources are characterized by the *same* wage-offer distribution. He then shows that the mean wage conditional on having accepted an offer from the network is *lower* than the mean wage conditional on having accepted one from the formal channels, if and only if the average number of offers from the network is *greater* than the average number of offers from formal channels. This initially counter-intuitive result is actually quite intuitive. As Montgomery explains suppose the formal channels almost never generate an offer while the network almost always yields an offer. Then almost all workers receive an offer from the network, but very few also receive one from formal channels. Therefore, *ex post*, those who accepted an offer from formal channels almost definitely chose the best of *two* offers, while those who accepted an offer from the network almost all chose the *one* offer they had. Consequently, on average, even though the network is stronger than the formal channels, those in jobs found through formal channels have higher wages than those in jobs found through the network.

We extend Montgomery's model to allow the network and formal channels to have *different* wage-offer distributions. Our extension is important because, as discussed in the introduction, previous studies have highlighted various reasons for these offer distributions to differ in either direction. Our model allows for either possibility.

We now describe our model in detail. Consider a new entrant looking for a first job. He has two sources of job offers, his network and formal channels. We simplify Montgomery's model by limiting the number of potential wage-offers from each source to at most one. Given that we apply our model to recent immigrants who have been in the host country for only about six months, we believe that this assumption is not unduly restrictive. Few will have received multiple offers through a single mechanism.[3]

We adopt a single-period (static) model. This allows us to easily model the possibility that a subset of new entrants will simultaneously hold multiple offers (two in our model) from firms at which they are not yet employed, something that is much more difficult to capture in a continuous time framework. We use a static model because recent immigrants are likely to be very impatient when it comes to transitioning into first jobs. Similarly to Burdett and Mortensen (1998), workers in our model always accept the first offer they receive if they receive a single offer. We depart from that model by allowing for the possibility that the worker may hold two offers simultaneously while not employed. In a standard sequential search model, we would have to allow the arrival rate of offers to affect the reservation wage. While, consistent with the fact that two-thirds of them are heads of households, we see little evidence that our sample of immigrants is turning down offers or targeting relatively high-wage jobs. We discuss later how endogenizing the reservation wage would affect our results.

We assume that all new entrants have the same value of leisure, which, without loss of generality, we normalize to zero. Wage offers rain down upon new entrants. Given that an entrant's reservation wage is his value of leisure, if he receives a single offer he accepts it, and if he receives more than one offer, he chooses the one with the highest wage.

With probability p_n he receives an offer from his network, and with probability p_f he receives one from formal channels. p_n characterizes the strength of his network. The higher the value of p_n, the stronger is his network. Let $F_n(w)$ and $F_f(w)$

[3]As an admittedly imperfect test of this hypothesis we looked at data on job turnover within six months since arrival in Canada. Only 15 percent of recent immigrants had worked in two jobs since arrival, and only 4 percent in three or more jobs. Moreover, 31 percent of recent immigrants had never been employed throughout the first six months since arrival.

denote the wage offer distributions of the network and formal sources, respectively. Both are defined over the positive real line.[4] If a worker receives only one offer, he accepts it; if he receives two offers (one from each source), he chooses the higher of the two; and if he receives no offers, he remains unemployed.

The mean wage conditional on receiving at least one offer is,

$$E(w|N \geq 1) = \frac{p_f(1-p_n)E(w_f) + p_n(1-p_f)E(w_n) + p_f p_n E(w|N=2)}{(p_f + p_n - p_f p_n)}. \quad (1)$$

where N is the number of offers received, and, $E(w_f)$ and $E(w_n)$ are the means of the formal and the network wage-offer distributions, respectively. Note that improvements in either the network strength, p_n, or the offer probability of the formal channels, p_f, could lower the mean wage conditional on being employed, $E(w|N \geq 1)$. For example, if most network offers are lower than formal offers, an increase in network strength could lower the mean wage among those employed. Of course, if we account for unemployed individuals, a higher probability of either type of offer must make workers better off, an auxiliary prediction that we confirm in the results section.

The mean wage conditional on having accepted an offer received through the network is,

$$E(w|n) = \frac{(1-p_f)E(w_n) + p_f \Pr(w_n > w_f)E(w_n|w_n > w_f)}{(1-p_f) + p_f \Pr(w_n > w_f)} \quad (2)$$

which is independent of network strength, p_n. This is because, for a fixed distribution, the mean value of a draw from the distribution does not depend on the probability of getting to make the draw. Similarly, the mean wage conditional on having accepted an offer from the formal channels is,

$$E(w|f) = \frac{(1-p_n)E(w_f) + p_n \Pr(w_f > w_n)E(w_f|w_f > w_n)}{(1-p_n) + p_n \Pr(w_f > w_n)}$$

which is increasing in p_n. It follows that the difference between the mean wage

[4] There is no loss of generality from ignoring negative wage offers that all workers would reject.

conditional on employment in a job found through the network and the mean wage conditional on employment in a job found through formal channels (the mean *network wage premium*), is decreasing in network strength, p_n.

2.1 Effect at Percentiles of the Observed Wage Distributions

Our argument applies equally to percentiles of the observed wage distributions**.** To show this we first establish the following proposition in which we show that the c.d.f. of the *observed* formal wage distribution, $F_f(w|f)$, is decreasing in network strength, p_n. For simplicity we assume that the formal and network wage distributions have a common support. The result goes through *mutatis mutandis* if they do not.

Proposition 1 *Let $F_f(w|f)$, the observed formal wage distribution, be continuous on $[a,b]$ with $F_f(a|f)=0$ and $F_f(b|f)=1$. Then $d(F_f(w|f))/dp_n<0$ for $a<w<b$ and $d(F_f(w|f))/dp_n=0$ for $w=a,b$.*

Proof. As defined earlier, let $F_n(w)$ and $F_f(w)$ be the wage-offer distributions of the network and formal sources, respectively. Let $f_n(w)$ and $f_f(w)$ be the corresponding offer densities. Then the c.d.f. of the observed formal wage distribution, $F_f(w|f)$, (i.e. the distribution conditional on having accepted a formal offer), is given by,

$$\begin{aligned} F_f(w|f) &= \frac{\int_a^w (1-p_n+p_nF_n(x))f_f(x)dx}{\int_a^b (1-p_n+p_nF_n(x))f_f(x)dx} \\ &= \frac{F_f(w)-\int_a^w p_n(1-F_n(x))f_f(x)dx}{1-\int_a^b p_n(1-F_n(x))f_f(x)dx} \end{aligned}$$

$$\frac{d}{dp_n}\left(\frac{F_f(w)-\int_a^w p_n(1-F_n(x))f_f(x)dx}{1-\int_a^b p_n(1-F_n(x))f_f(x)dx}\right)=\frac{\int_a^w F_n(x)f_f(x)dx-F_f(w)\int_a^b F_n(x)f_f(x)dx}{\left(1-\int_a^b p_n(1-F_n(x))f_f(x)dx\right)^2}$$

Inspection of the numerator proves that $d(F_f(w|f))/dp_n=0$ for $w=a,b$. Next, consider

$$\frac{\int_a^w F_n(x)f_f(x)dx}{\int_a^b F_n(x)f_f(x)dx} = \frac{\int_a^w F_n(x)f_f(x)dx}{\int_a^w F_n(x)f_f(x)dx + \int_w^b F_n(x)f_f(x)dx}$$

From the first mean value theorem of integration, there exists weights ω_1.and ω_2, such that

$$\frac{\int_a^w F_n(x)f_f(x)dx}{\int_a^b F_n(x)f_f(x)dx} = \frac{\omega_1 F_f(w)}{\omega_1 F_f(w) + \omega_2(1 - F_f(w))}$$

where

$$0 < \omega_1 < F_n(w) < \omega_2 < 1$$

for $a < w < b$. It follows that

$$\frac{\int_a^w F_n(x)f_f(x)dx}{\int_a^b F_n(x)f_f(x)dx} < F_f(w)$$

Therefore,

$$\frac{dF_f(w|f)}{dp_n} = \frac{\int_a^w F_n(x)f_f(x)dx - F_f(w)\int_a^b F_n(x)f_f(x)dx}{\left(1 - \int_a^b p_n(1 - F_n(x))f_f(x)dx\right)^2} < 0.$$

■

The proposition establishes that except for the highest and lowest wages, the percentile associated with any wage of the observed formal wage distribution is reduced when network strength increases. The intuition is straightforward. Any network offer beats a formal offer if it is greater than the formal offer, but it has no effect on the acceptance of formal offers above it. Most network offers will beat a very low formal offer, but not a very high one. On average, therefore, a network offer reduces the probability that the worker accepts a low formal offer by more than it reduces the probability that the worker accepts a high formal offer. The observed formal wage distribution shifts to the right. Since the percentile of the observed formal wage distribution associated with each wage is reduced as network strength increases, the wage associated with each percentile goes up. On the other hand, the c.d.f. of the *observed* network wage distribution, $F_n(w|n)$, is independent of p_n, because, conditional on receiving a network offer, the probability that the offer will be better than a formal offer is independent of p_n. We, therefore, have the following corollary.

Corollary 1 *The difference between any percentile (except the highest and the lowest percentiles) of the observed network wage distribution and the same percentile of the observed formal wage distribution decreases as network strength increases.*

This result, which has not been discussed in previous literature, suggests a potentially more powerful test of the model: since there is no effect of network strength on the network premium at the highest and lowest percentiles, there must be some percentile at which the effect is larger than it is at the mean. We use simulations to get a sense of where the effect of network strength is likely to be the largest. We choose offer probabilities to match the proportions in the data of those never employed; in formal jobs; and in network jobs. We also assume that both the network and the formal log wage distributions are normal with zero mean. We find that across nineteen equidistant percentiles (ranging from the 5th to the 95th), when the standard deviations for both distributions are equal, the largest effect on the network premium of an increase in network strength is at the 25th percentile. For other plausible ratios of the standard deviations (ranging from 0.5 to 2), we find that the largest effect lies within the 10th to 30th percentile range. Based on these simulations, we expect that, as network strength increases, the decrease in network premium should be highest below the median and probably somewhere around the first three deciles.[5]

2.2 Summary of Predictions

In our setup where a worker can receive at most one offer from each source, and where the network and formal wage-offer distributions may be different, the model has the following predictions:

[5] Detailed results from these preliminary simulations can be made available on request.

1. The mean of the *observed* network wage distribution is independent of network strength.

2. The mean of the *observed* formal wage distribution is increasing in network strength.

3. Conditional on being employed**,** the mean network wage premium is decreasing in network strength (follows from predictions 1 and 2).

4. The difference between any percentile (except the highest and the lowest percentiles) of the observed network wage distribution and the same percentile of the observed formal wage distribution is decreasing in network strength.

Predictions (3) and (4) are the main testable predictions of our model. As discussed in section 3, compared to predictions (1) and (2), the empirical framework to test predictions (3) and (4) is more robust to concerns about unmeasured differences between individuals with strong and weak networks.

2.3 Threats to our Theory: Other Network Mechanisms

In our model, the strength of a network is characterized by the probability with which it provides a job offer. In other words, we believe that an effective network influences observed wages by increasing the probability of generating a network offer. However, there are other ways in which a network can influence wages. In this subsection, our focus is on scenarios wherein our main testable implication, namely, the network wage premium decreases with network strength, might be confirmed in the data even though the principal mechanism through which a stronger network influences wages is *not* by an increase in the probability of generating an offer. Although we discuss scenarios where we might fail to find empirical support for our model in spite of our mechanism being operative ('false rejections'), we are primarily concerned about incorrectly accepting our theory about how networks operate.

Given that our empirical measure of network strength is the presence of a close tie we address the following concerns: effect of a close tie on the wage-offer distributions, its effect on the offer probability from formal channels, receiving multiple network offers, the possibility of sequential search, and worker heterogeneity.

Consider first the potential effects of a close tie on wage-offer distributions. One possibility is that a close tie worsens the network offer distribution: for example, if social norms dictate that the new immigrant should work for his relative, then the latter may exploit the situation and offer him a low wage. In this case, the network premium would decrease in network strength, but for a reason different from the one described in our model. However, note that the observed network wage distribution would then be worsening in network strength, contradicting prediction 1 above that it is independent of network strength. When we check for this in our data (section 5.3.1), we find no evidence in its support**.** Another possibility is that a close tie improves the formal offer distribution. If this is true, we would again incorrectly confirm our theory. However, in that case, the presence of a close tie would imply an increase in the likelihood of being in a job found through formal channels, something we do not find in our data.

Second, consider the possible effect of a close tie on the offer probability from formal channels. Because workers with a close tie expect to receive an offer from their network, they might endogenously reduce their search effort through formal channels. This would then reduce the probability of receiving a formal offer, which would in turn reinforce our prediction. Since this is an endogenous response to the mechanism we identify, we do not consider it to be problematic.

Yet another possibility is that a close tie increases the probability of receiving multiple offers from the network. This would result in an improvement in the effective network offer distribution. At the same time, the distribution of accepted formal offers is still increasing in network strength because of the mechanism we identify, namely, an increase in the pool of offers to choose from among those accepting formal source jobs. If the effect of an improvement in the effective network offer distribution dominates the effect on those accepting formal offers, then, we might fail to confirm our prediction that the network premium falls as network strength rises. This is a situation where even though a stronger network is characterized by an increase in the probability of receiving a greater number of network offers, we do not find evidence to support our theory. However, as stated earlier, we are less apprehensive about such 'false rejections.'

Another concern is that we consider a single period model and do not allow the arrival rate of offers to depend on employment status. If search were sequential, workers' reservation wages when unemployed might be sensitive to the arrival rate of offers. It is certainly possible to construct examples in which a higher arrival rate of offers in one or both states would change the reservation wage while unemployed. If the offer distributions from the two sources are similar, which our estimates (shown later) suggest they are, changes in the reservation wage should not greatly affect our predictions.

Finally, we have considered a group of homogeneous entrants, whereas in real life they may differ in their skill level. This raises two issues. The first is that the presence of a close tie might be associated with a network premium for reasons unrelated to an increase in the probability of a network offer. For example, if the presence of a close tie only helps high-skill immigrants find jobs through formal channels, then the network-formal skill differential would decrease in the presence of a close tie, and this would lead us to falsely accept our model. However, all such mechanisms would imply that both network and formal wages are affected by network strength, which our data do not support. The second issue is that, even if the presence of a close tie is characterized by an increase in the probability of a network offer for both low- and high-skill immigrants, it could increase this probability by different magnitudes for the two groups. If the presence of a close tie increases the probability of a network offer for low-skill immigrants by more than it does for high-skill immigrants, then its presence will lower the mean skill level of immigrants found in network jobs by more than it does of immigrants found in formal jobs. This would then reinforce our prediction that the network premium is decreasing in network strength. It is important to note that this is not problematic as the mechanism is endogenous to an increase in the probability of a network offer. On the other hand, if a close tie increases the probability of a network offer for low-skill immigrants by less than it does for high-skill immigrants, the change in skill distribution could obscure the effect of an increase in the probability of a network offer on individual immigrants and we would falsely reject our model. In our empirical work we control, as much as possible, for individual heterogeneity. Nevertheless, it is impossible to know whether the difference in unmeasured heterogeneity between immigrants finding jobs through the two mechanisms is greatly affected by network strength, and, if it is, whether this "difference-in-differences" is an endogenous response to the increased probability of a network offer (in which case it is not problematic) or it reflects factors outside the model.

3 Empirical Framework

Our close tie measure is closely related to the concept of strong ties used in sociology (Granovetter 1973). In the data, close tie **(**CT) is a binary variable. It refers to whether the recent immigrant had *at least one* relative or friend already living in Canada when he first arrived. $CT = 1$ if he reports that he had at least one such social tie, otherwise $CT = 0$. Note that we refer to this measure in the singular (as close tie and not close ties), even though the immigrant may have had more than one such social tie.

Validation of Close Tie as a measure of Network Strength: Recall that our theoretical concept of network strength is the probability of receiving a wage-offer from the network. Network strength should therefore be associated with a higher probability of being in a job found through the immigrant's network, a lower probability of being in a job found through the formal channels, and a lower probability of never having been employed since arrival in Canada. In addition, if we impute a very low wage to those who have never been employed, the measure should also be associated with higher wages: stronger networks should make workers better off. These predictions probably apply to a wide class of models and are not specific to our characterization of a strong network. Nevertheless, it is important to check that they hold in data because if they don't, it implies that our empirical measure of network strength is not valid. We use multinomial logit to examine how close tie is associated with the three job search outcomes, namely, never employed since arrival, u; found first job through the network, nj; and found first job through formal channels, fj. The log-odds ratio for this regression is given by,

$$\ln \frac{P^l_{ijk}}{P^u_{ijk}} = \delta^l_0 + \delta^l_1 CT_{ijk} + \delta^l_2 X_{ijk} + \omega^{1l}_j + \lambda^{1l}_k \tag{3}$$

where the subscripts refer to immigrant i, country of birth j, and area of residence k; $l \in \{nj, fj\}$, X is a set of additional controls that is likely to influence the search outcome; and ω^1_j and λ^1_k are country of birth and area of residence dummies, respectively.

To look at the association between close tie and wages, we estimate a set of quantile wage regressions that include those who have *never been employed* since arrival. The regression specification is given by,

$$\ln w'_{ijk} = \alpha_0 + \alpha_1 CT_{ijk} + \alpha_2 X_{ijk} + \omega^2_j + \lambda^2_k + \upsilon_{ijk}. \tag{4}$$

where w' is the wage in the immigrant's first job if he was ever employed after arrival, and it is an imputed low wage if he was never employed during that time. The remaining variables are defined as in equation (3) above. For CT to be a valid measure of network strength, α_1 must be positive.

To preview the results, close tie satisfies the conditions to be considered a valid measure of network strength.

Network Premium and Close Tie: After having validated our measure of network strength, we test our model's main implication: that the network wage premium decreases in network strength. To do this, we consider immigrants who were employed at least once after arrival, and look at (log) wages in their first job. Unlike equation (4), we exclude immigrants never employed after arrival. OLS is used to test the implication at the mean, while quantile regressions are used to test it at the nine deciles. We estimate a standard Mincerian wage equation augmented with the close tie variable (CT), the *network job* variable (NJ) and these two variables interacted. NJ is a binary measure of whether the immigrant found his first job through his network: $NJ = 1$ if the first job was found using his network, and $NJ = 0$ if it was found using the formal channels. The equation we estimate is given by the following difference-in-differences specification,

$$\ln w_{ijk} = \theta_0 + \theta_1 CT_{ijk} + \theta_2 NJ_{ijk} + \theta_3 (NJ_{ijk} * CT_{ijk}) + \theta_4 X_{ijk} + \omega_j^3 + \lambda_k^3 + \zeta_{ijk} \quad (5)$$

where, conditional on being employed at least once since arrival, w is the wage in the immigrant's first job in Canada.

Following section 2.2, the main predictions of our model are:

1. $\theta_1 + \theta_3 = 0$: The observed network wage is independent of network strength.
2. $\theta_1 > 0$: The observed formal wage is increasing in network strength.
3. $\theta_3 < 0$: Conditional on being employed, the network wage premium is decreasing in network strength.

θ_1 might be positive for reasons unrelated to a higher probability of receiving a network offer. If, for example, immigrants with a close tie are positively (negatively) selected than those without a close tie, then θ_1 could be spuriously positive (negative). Essentially the same concerns apply to $\theta_1 + \theta_3$. Thus, the identifying assumptions for testing the first two predictions are overly severe.

Consider the third prediction, $\theta_3 < 0$. For a consistent estimate of θ_3, we require a condition similar to that in a standard difference-in-differences design. We require that if a close tie *does not increase* the probability of receiving an offer from the network, then the difference in the unmeasured characteristics of immigrants with and without a close tie should be independent of whether they happen to find their job through their network or through formal channels:

$$\begin{aligned} E(\zeta_{ijk}|NJ_{ijk} &= 1, CT_{ijk} = 1, Z_{ijk}) - E(\zeta_{ijk}|NJ_{ijk} = 1, CT_{ijk} = 0, Z_{ijk}) = \\ E(\zeta_{ijk}|NJ_{ijk} &= 0, CT_{ijk} = 1, Z_{ijk}) - E(\zeta_{ijk}|NJ_{ijk} = 0, CT_{ijk} = 0, Z_{ijk}) \quad (6) \end{aligned}$$

where

$$Z_{ijk} \equiv \left[X_{ijk}, \omega_j^3, \lambda_k^3\right]$$

As discussed in section 2.3, it is highly likely that there exist differences across skill categories, in the magnitude of an increase in the probability of network offer due to the presence of a close tie. As network strength increases, this would then result in an endogenous change in the skill composition of immigrants finding jobs through the two sources. Given that this is an endogenous change, it is not problematic for our analysis. If, however, the change in skill composition is due to exogenous factors unrelated to an increase in the probability of receiving an offer from the network, then it can potentially lead us to incorrectly accept our model. Although, we include extensive controls for individual heterogeneity, we can never be certain that the composition of unobservable skills of immigrants finding jobs through the two sources does not change in the presence of a close tie. However, we can test whether there is evidence of a such a change in their observable characteristics. As noted above, such a change (if endogenous) is consistent with our model and would not automatically invalidate our approach. But, the absence of any change would make it more plausible that there was no exogenous shift in their unmeasured characteristics. We present evidence on this issue in sections 5.3.2 and 5.3.3.

4 Data

Our data come from the Longitudinal Survey of Immigrants to Canada (LSIC), collected by Statistics Canada, and Citizenship and Immigration Canada. The LSIC consists of immigrants older than 15 years, who arrived in Canada between October 1, 2000 and September 30, 2001. It is a longitudinal survey with three waves: immigrants are interviewed at six months, two years and four years since arrival. We use only the first wave and refer to immigrants in this wave as *recent immigrants*. Our target population is principal applicants (persons upon whom the approval to immigrate was based) and their dependants in the 15 to 64 age group, who are in the labor force and who live in metropolitan areas in Canada.[6] We exclude immigrants who were in prearranged jobs,[7] and those who were self employed or in family businesses.[8] Finally, we limit the analysis to immigrants from metropolitan areas and from source countries with at least ten immigrants in the LSIC sample.[9] The final LSIC estimation sample consists of 6524 recent immigrants, from 64 different source countries and residing in 23 different metropolitan areas across Canada.

4.1 Descriptive Analysis

Table 1 presents summary statistics for recent immigrants in our estimation sample, at six months since arrival. Column (1) shows statistics for the entire cohort of recent immigrants, while columns (3) and (4) condition on whether the immigrant has a close tie. 89 percent of the recent immigrants have a close tie or not. A network job is one that the respondent reports having found through a relative or friend, while a formal job is one found through other methods such as contacting the employer directly, responding to newspaper advertisements, employment agen-

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[6] A census metropolitan area (CMA), or a census agglomeration (CA), is formed by one or more adjacent municipalities centered on a large urban urban core. In case of a CA, the population of the urban core is at least 10,000, and in case of a CMA, it is at least 100,000. CMAs and CAs are collectively referred to as metropolitan areas.

[7] When asked about their first jobs, 7.2 percent of the recent immigrants report being in prearranged jobs. We exclude these immigrants from our analysis for two reasons. First, we believe that the nature of job search for them is fundamentally different from that for those who arrive without a job. Second, immigrants with prearranged jobs are different from other immigrants in terms of their observed characteristics. They are less likely to have a close tie, be female, be married, and have kids, but are more likely to be older, know English, have lived in Canada before migration, be the principal applicant, have an economic visa, and have been a manager or a professional in their job before migration.

[8] 2.1 percent reported being self-employed, and 0.6 percent reported being in family businesses.

[9] We lose 5.9 percent of the remaining LSIC sample due to this restriction. Reducing this cutoff below ten resulted in very large standard errors in our quantile regressions that contain country of birth and metropolitan fixed effects. Later, when we estimate wage regressions conditional on being employed, we further restrict the LSIC estimation sample to include only those immigrants with at least ten recent immigrants with *positive wages* from their country of birth, and, separately, with positive wages in their metropolitan area.

cies, the internet and referral from another employer or a union.[10] At six months after arrival, 31 percent report their first job to be a network job, 39 percent report it to be a formal job, and the remaining 31 percent had not yet found a job. It is interesting to note that while 32 percent of immigrants with a close tie found their first job using their network, the corresponding figure for those without a close tie is only 19 percent. Recent immigrants are highly educated as 65 percent report having a Bachelor's or higher degree, and 73 percent entered Canada on an economic visa. These figures are higher for immigrants without a close tie: 72 percent have a Bachelor's or higher degree and 87 percent are on an economic visa. Despite being highly skilled, the average weekly wage for a recent immigrant in his first job (the earnings measure used in this study) is low: 396 Canadian dollars per week.[11]

Two things must be noted at this point. First, the first job being a network job ($NJ = 1$) does not necessarily imply the presence of a close tie ($CT = 1$), and vice versa. An immigrant may not have a close tie but may have still found a network job, perhaps through a friend made *after* migrating to Canada or through a relative/friend *not* living in Canada. Conversely, in spite of the presence of a close tie, his first job may have been found through formal channels or he may still be unemployed. Second, the dichotomous measure of the 'use of the social network' captured by the variable NJ, may not be perfectly related to the theoretical concept it wishes to encapsulate. For example, suppose that a friend tells me about a job opening, and I apply and get the job. Do I report that I found the job through a friend $(NJ = 1)$, or that I applied directly to the employer $(NJ = 0)$? Thus, admittedly, our measure of the *use of network* is imperfect. However, in contrast

[10]The survey questions used to construct the *network job* variable are as follows:
How did you find this job? 1) Contacted employer directly? 2) Job found by a friend? 3) Job found by a relative? 4) Placed or answered newspaper ad? 5) Employment agency (including Canada Employment Centre)? 6) Referral from another employer? 7) Internet? 8) Union? 9) Other? The response to each question could be either a 'Yes' or a 'No', and it was admissible to answer 'Yes' to multiple questions (although only 4 percent of the respondents did so). If the answer to either question 2 or question 3 was 'Yes', then $NJ = 1$, otherwise $NJ = 0$.

[11]Use of weekly wage, instead of hourly wage, would have been problematic for our estimations if the difference in hours worked between network and formal jobs depended on whether or not the immigrant had a close tie. We check for this and do not find evidence in its support.

with much recent research (e.g. Bayer et al 2008; Dustmann et al 2015; Hellerstein et al 2011), we measure network use directly and therefore avoid the need to infer network use from the clustering of immigrants.

5 Results

We first provide evidence to support the use of close tie as a valid measure of network strength. Then we report estimates from the difference-in-differences specification to test the main implication of our model. This is followed by some checks to rule out alternate theories that could potentially explain our findings. Finally, we present structural estimation results to provide additional support for the mechanism that we wish to highlight, namely, that the presence of a close tie operates by increasing the likelihood of receiving a network offer.

5.1 Close Tie as a Measure of Network Strength

The first three columns of table 2 look at the job search outcome for recent immigrants during the first six months since arrival. If the immigrant was ever employed during this time, then only his first job is considered. Using a multinomial logit (equation (3)), the table gives the marginal effects of close tie on the probability of each search outcome. Close tie is strongly related to the first job being a network job. At the means of the independent variables, the presence of a close tie is associated with a 8.6 percentage point increase in the likelihood of being in a network job. It is also associated with a 4.5 percentage point decrease in the likelihood of being in a formal job and a 4.1 percentage point decrease in the probability of never being employed, although the latter falls short of statistical significance (p-value of 0.116). Thus, the relation between job search outcomes and close tie is broadly consistent with our expectations.

Columns 4 and 5 of table 2 present estimates from quantile regressions at the 50th and 75th percentiles (equation (4)). The dependent variable is the (log) wage in the immigrant's first job if he was ever employed during the first six months in Canada, and it is an imputed low wage if he was never employed during this time.[12] The presence of a close tie is associated with 8.6 percent higher wages at the 75th percentile. The magnitude of the effect at the median is 9.6 percent but falls well short of significance at conventional levels.

Based on the results in table 2, the close tie measure passes our basic tests. It is associated with increased job-finding through the network and reduced employment through formal channels, and the point estimate suggests that it is also associated with a lower probability of having never been employed. Moreover, it is also associated with higher wages when treating those who have never been employed as having a low wage, at least at the third quartile. This, of course, does not mean that close tie works in the manner proposed in our theoretical model, but rather that it has passed the minimal conditions consistent with its interpretation as a measure of network strength as we conceptualize it.

5.2 Network Premium and Close Tie

Table 3 shows the results from estimating equation (5): conditional on being employed, the wage equation augmented with our measure of network strength (close tie, CT), method of finding the first job (network job, NJ) and the interaction between these two variables. The dependent variable is the weekly wage in the immigrant's first job in Canada obtained within six months of arrival. Column (1) presents the OLS results, while columns (2) through (10) present quantile regression results at the nine deciles.

Our model predicts that the mean wage in formal jobs should be increasing in network strength, while the mean wage in network jobs should be unrelated to it.

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[12] Standard errors for this and all other quantile regressions are calculated using a clustered bootstrap. Unless otherwise stated bootstrap estimates are based on completed replications out of 600 draws from 427 metropolitan-country of birth clusters.

It was not possible to estimate (4) at the first quartile because 31 percent of the recent immigrants have never been employed. Therefore, we only present results for the second and the third quartiles (50th and 75th percentiles).

As discussed in section 3, assuming that unmeasured individual characteristics are uncorrelated with close tie is very strong. However, for completeness, we nevertheless mention our results in this regard. Using OLS, the presence of a close tie is associated with an 9.6 percent increase in the mean formal wage. Further, quantile regressions show that the association between close tie and formal wage is positive at all deciles, except at the ninth, though it is not always statistically significant. It is large and statistically significant at the first, second, fourth and fifth deciles.

The effect of network strength on mean network wage is measured by the sum of the coefficients on close tie, and close tie interacted with network job. There is no consistent pattern to this estimate. It is positive in OLS, negative at the first four deciles and positive at the remaining higher deciles. However, in all cases the estimates are statistically insignificant at conventional levels and are generally small in absolute value.

For reasons discussed earlier, our main focus is on the interaction term. Our model predicts that the coefficient on the interaction term is negative at the mean and at all percentiles (except the highest and the lowest percentiles). Also, our initial simulations suggest that it may be more negative at percentiles below the median. For OLS, at the first through the sixth deciles, and at the eighth decile, the interaction term is negative, as predicted, though not always statistically significant. Although, the interaction term is positive at the seventh and ninth deciles, in these cases it is statistically insignificant. Column (3), pertaining to wages at the second decile conforms closely with the predictions of our model. There is a 25.2 percent decrease in network premium in the presence of a close tie and this is statistically significant at the 0.05 level. There is a 11.4 percent decrease at the fourth decile and it is statistically significant at the 0.10 level. Finally, we bootstrapped a joint test of the hypothesis that the interaction term in all nine deciles is zero against the one-tailed alternative that some are negative. We reject the null at 0.01 level of significance. Overall, we find evidence in support of our theory that the network wage premium is decreasing in network strength.[13]

[13]At the second decile, we examined the interaction term separately for men, women; high education, low eduation; 30 and younger and over 30. In all cases the coefficient on the interaction

5.3 Testing Threats to the Theory

As discussed in section 2.3, most alternate explanations for a decrease in the network premium as network strength increases require that the observed network wage distribution be inferior in the presence of a close tie. We test for this below. We also test for whether *the difference* in observable characteristics of immigrants finding jobs through the network and formal channels *changes* in the presence of a close tie. While the presence of such a change is not inconsistent with our model, its absence would make it more likely that there was no exogenous shift in unobservable characteristics either. Finally, we examine whether the interaction coefficient changes when we omit observable skills.

5.3.1 Network Wages and Close Tie

As already noted, for none of the regressions in table 3, is the sum of the coefficients on close tie, and close tie interacted with network job, statistically significant, and it is generally small in magnitude. This suggests that the mean network wage is independent of the presence of a close tie.

As a further test, we restrict the sample to those having network jobs and conduct the Kolmogorov-Smirnov test of equality of network wage distributions (conditional on observables) among those with and without a close tie. Once again, we find no evidence of a difference in these distributions, making it more plausible that the network premium decreases with network strength due to the mechanism described in our theoretical model.

5.3.2 Difference-in-Differences for Observed Characteristics

Table 4 shows the results for a difference-in-differences specification, where an explanatory variable from equation (5) is regressed on close tie, network job and

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term was negative, however, bootstrapping the standard errors was unreliable because of the small sample sizes.

their interaction.

OLS results in columns 1 through 8 show that for eight of the nine observed characteristics examined in table 4, the network-formal characteristic-differential does not change with close tie. Column (9) presents the coefficients from an ordered logit model of educational attainment. The interaction coefficient is negative, indicating a decrease in network-formal education differential in the presence of a close tie. This, by itself, does not invalidate our testing strategy. Also it is not surprising to find that one of nine coefficients is significant at the .05 level, and the t-statistic is well below the Bonferroni critical value for nine tests. Unfortunately, there is no way to know for sure whether there is an unobservable skill differential, and, if so, whether it is due to exogenous factors.

5.3.3 Excluding Observed Skills

Here we examine the effect of excluding the observed characteristics from equation (5). In effect this asks whether an appropriately weighted sum of observed characteristics is correlated with the interaction term. While the absence of such a correlation would not guarantee that there is no correlation between unmeasured characteristics and the interaction, it would make the assumption more plausible.

Table 5 shows the effect of dropping variables that control for skills from the wage equation. The most important point to note is that the results look quite similar to those with controls for observed skills.[14] In particular, while controlling for skill makes the coefficient on the interaction term less negative for OLS, it makes it more negative at the second decile, and both coefficient changes are relatively small in magnitude. Moreover, it is important to remember that we have an extensive set of controls for skill. In particular, besides level of education and visa category, we also control for prior occupation in eight categories and knowledge of English and French. While it remains possible that there is an important measure of skill that is correlated with the interaction term, the fact that excluding this extensive set

[14] Also, for the regression at the second decile excluding observed skills, although the interaction term is not significant at conventional levels, the p value is 0.110.

of controls does not noticeably alter the magnitude of the interaction coefficients, gives us a reasonable level of confidence in them.

6 Structural Model

Our theoretical model characterizes a stronger network by a higher probability of generating a network offer and assumes that the network wage-offer distribution remains unchanged irrespective of whether the network is strong or weak. As discussed in section 2.3, there could be other ways to characterize a stronger network. In this section we investigate whether an alternate model, in which network strength is characterized by different network wage-offer distributions, fits the data better. We build a simple structural model and estimate it using maximum likelihood. This allows us to uncover the underlying wage-offer distributions and offer probabilities from each source. The structural estimates provide evidence to support our conclusion that the primary role of a close tie is to increase the likelihood of a network offer rather than to change the network offer distribution.

We also note that estimating the structural model provides an additional test of the importance of unmeasured skills for our reduced-form results in table 3: if the unobserved skills of workers in network jobs depend on whether they have a close tie, then, this should be reflected as different network offer distributions depending on whether or not a close tie exists.

6.1 The Model

Once again, we model the first period of a multi-period search process. We assume that the immigrant receives at most one offer from each source, according to the following probabilities; p_f from the formal channels, p_s from his network if it is strong (in the presence of a close tie) and p_w from his network if it is weak (in the absence of a close tie). Each log wage, ω, is drawn from a source specific offer distribution given by

$$\omega_{ij} = X_i\beta + \alpha_j + \varepsilon_{ij}, \qquad \varepsilon_{ij} \sim N(0, \sigma_j^2) \tag{7}$$

where i denotes the immigrant and j denotes the source (formal channels f, strong network s, and weak network w). Thus, α_j is a source-specific factor shifting the mean of the offer distribution. We also allow the variance of the error, σ_j^2, to vary across sources. We assume that the errors are independent across i and j.

To derive the likelihood function, note that the probability that a worker with a strong network ($CT = 1$) is unemployed (u) is,

$$LF(u|CT = 1) = (1 - p_f)(1 - p_s) \tag{8}$$

and the probability that a worker with a weak network is unemployed is,

$$LF(u|CT = 0) = (1 - p_f)(1 - p_w) \tag{9}$$

The probability that a worker with a strong network is earning a given wage (ω) and is working in a network job ($NJ = 1$) is,

$$LF(\omega, NJ = 1|CT = 1) = \left[p_s\left\{(1 - p_f) + p_f\Phi\left(\frac{\alpha_s - \alpha_f + \varepsilon_{is}}{\sigma_f}\right)\right\}\right]\phi_s(\varepsilon_{is}) \tag{10}$$

The last term, $\phi_s(\varepsilon_{is})$, is the standard normal density of the network offer when the network is strong. The term in square brackets is the probability of receiving and accepting a network offer when the network is strong. This is itself a product of the probability of receiving a network offer when the network is strong (p_s), and the probability of either not receiving a formal offer ($1 - p_f$), or receiving an inferior formal offer ($p_f\Phi$), where Φ is the standard normal c.d.f. and is derived by noting that the formal offer is rejected if it is less than the network offer. Thus Φ is the probability that

$$X_i\beta + \alpha_f + \varepsilon_{if} < X_i\beta + \alpha_s + \varepsilon_{is} \tag{11}$$

or

$$\Pr(\frac{\varepsilon_{if}}{\sigma_f} < \frac{\alpha_s - \alpha_f + \varepsilon_{is}}{\sigma_f} | \varepsilon_{is}) \text{ where } \frac{\varepsilon_{if}}{\sigma_f} \sim N(0,1) \tag{12}$$

with the errors independent across the sources.

The probability of earning a given wage and working in a network job when the network is weak, and the probabilities of formal employment when the network is strong and weak, can be similarly expressed. Taking logs and summing across observations gives the log likelihood function which we maximize with respect to the offer probabilities (p_f, p_s, p_w), and the means and standard deviations of the offer distributions (α_j, σ_j)

6.2 Structural Parameter Estimates

The first column of table 6 gives the results of estimating the most flexible specification, wherein we allow the network offer distribution to depend on network strength, and also allow the formal offer distribution to differ from the network distributions. We estimate that formal channels provide an offer with probability 0.47. Strong and weak networks do so with probabilities, 0.45 and 0.25, respectively, which are significantly different from each other. This suggests that of the immigrants with a strong network (those with a close tie), about 21 percent get two offers, and about 29 percent get no offers. In contrast, of the immigrants with a weak network (those without a close tie), about 12 percent get two offers and nearly 40 percent get no offers. The means of the three distributions are quite similar.[15] The residual variances of the network offer distributions are somewhat, but not dramatically lower, compared to that of formal channels. More importantly, we cannot reject the hypothesis that the means of the strong and weak network offer distributions are the same ($t = 1.3$), nor the hypothesis that their standard deviations are the same ($t = -1.2$). Therefore, in the second column, we restrict the network offer distributions to be the same irrespective of network strength. Comparing the

[15]Note that the level of the means is arbitrary. These are essentially constant terms in a regression where the effects of the explanatory variables have been constrained to be the same across the three distributions.

log-likelihood values in the first two columns, we cannot reject the hypothesis that the network offer distribution is independent of network strength ($\chi^2(2) = 3.06$). This provides strong evidence for our conclusion that the presence of a close tie primarily influences wages by increasing the probability of generating a network offer, rather than by influencing the network offer distribution. As mentioned at the start of this section, the result that there is a single network offer distribution irrespective of whether the network is strong or weak also makes it less likely that differences in unmeasured skills are driving the results in table 3.

In column (2), the means of the network and formal offer distributions are not statistically different from each other. Although their standard deviations are statistically different, the numerical values differ only modestly from each other. Finally in the last column we restrict the network and formal offer distributions to be the same. Comparing the log-likelihood values in columns (2) and (3), this hypothesis is rejected ($\chi^2(2) = 52.03$), though from column (2) we know that the two distributions only marginally differ from each other.

Thus the results of the structural model are very much in line with our theoretical model: network strength, captured by the presence of a close tie, is associated with a greater likelihood of receiving an offer from the network. It is not associated with a large alteration of the network offer distribution.

Using the structural parameter estimates from column (2) of table 6, we also simulate the network wage premium, at the mean and at various deciles. This allows us to examine whether the results in table 3 can be reproduced using our structural parameter estimates of the underlying offer distributions and offer probabilities. The results are mixed.[16] On the one hand, for both the mean and each decile, the simulated coefficient on "Network Job*Close Tie" always falls within the confidence interval of the coefficient reported in table 3. On the other hand, the magnitude of the simulated interaction coefficients at the three lowest deciles is noticeably smaller than in table 3. This may indicate that network strength increases the likelihood of a low-wage offer, but the structural model does not have sufficient

[16] Simulation results available on request.

power to detect this effect.

7 Summary and Conclusions

In this paper, we draw on Montgomery 1992 to develop a theoretical model that describes how social networks operate in the job search process. We model the strength of a worker's network by the likelihood with which it provides him a job offer. Considering that a worker can find a job either through his network or through the formal (non-network) channels, we show that the network-formal wage differential is decreasing in network strength.

We test this implication on a nationally representative sample of recent immigrants to Canada. In the data, the presence of a 'close tie' (at least one relative or friend already living in Canada at the time of the immigrant's arrival), captures the concept of a stronger network as we have defined it. Using a standard difference-in-differences approach, we find that the network premium decreases with the presence of a close tie, thus confirming that close ties operate by increasing the probability of receiving a network offer. As we suggested was likely to be the case, evidence in favor of our model is especially strong at the lower end of the observed wage distribution (first four deciles). This might appear to suggest that close ties particularly increase the likelihood of low-wage offers, but we have shown this to be incorrect.

We estimate a simple structural version of the model that confirms that the primary role of close ties is to increase the probability of generating a wage offer from the network rather than to alter the distribution from which an offer is drawn. These estimates also suggest that the network and formal offer distributions differ only modestly, so that Montgomery's (1992) model, which relies on network and formal offer distributions being identical, may be applied to the data.

It is often argued that immigrants tend to cluster together because the presence of established immigrants facilitates assimilation of new arrivals, both in the labor market and in the social environment of the host country. We find that social networks, as embodied in relatives and friends already living in the host country, help recent immigrants find their first jobs. The mechanism through which such networks operate is by providing a larger number of job offers. Our analysis also suggests that such close ties do not influence the kind of job offers that immigrants receive. In other words, in the absence of close ties, recent immigrants would receive fewer offers, but the offers they do receive would be neither better nor worse than those they would have received had such ties been present. We have not addressed other issues related to immigrant assimilation, including the longer term labor market effects of social networks.

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Table 1: Recent Immigrants to Canada (at six months since arrival)

	All Recent Immigrants Mean (Std. Dev.)	Sample Size	Without Close Tie Mean (Std. Dev.)	With Close Tie Mean (Std. Dev.)
	(1)	(2)	(3)	(4)
Network Strength Measure				
Close Tie (CT)	0.89	6524		
Job Outcomes				
First Job is Network Job	0.31	6524	0.19	0.32
First Job is Formal Job	0.39	6524	0.44	0.38
Never Employed	0.31	6524	0.38	0.30
Weekly Wage in First Job (CAD)	396 (275)	4318	405 (347)	395 (266)
Explanatory Variables				
Female	0.43	6524	0.43	0.43
Age	34 (9)	6524	33 (8)	34 (9)
Married	0.76	6524	0.75	0.76
Number of children	0.83 (1.03)	6524	0.85 (0.99)	0.83 (1.03)
Speaks English Well	0.65	6524	0.63	0.65
Speaks French Well	0.12	6524	0.12	0.11
Lived in Canada Before	0.05	6524	0.06	0.05
Principal Applicant	0.68	6524	0.61	0.68
Education				
Less than High School	0.09	6488	0.06	0.09
High School	0.09	6488	0.06	0.10
Some College	0.05	6488	0.04	0.05
College	0.13	6488	0.13	0.12
Bachelor	0.43	6488	0.47	0.42
Master and above	0.22	6488	0.25	0.21
Visa Category				
Economic Visa	0.73	6456	0.87	0.71
Family Visa	0.23	6456	0.07	0.25
Refugee Visa	0.04	6456	0.05	0.04
Occupation before migrating				
Manager	0.02	6478	0.02	0.02
Professional	0.35	6478	0.38	0.35
Paraprofessional	0.13	6478	0.12	0.13
Clerical	0.02	6478	0.02	0.02
Laborer	0.002	6478	0.00	0.002
New Worker	0.23	6478	0.20	0.24
Student	0.10	6478	0.09	0.10
None	0.14	6478	0.16	0.14

LSIC sample has been appropriately weighted to reflect statistics for the target population.
Variation in the sample size (column 2) is due to differences in missing data across variables.
Weekly wage is only reported for those who were ever employed within the first six months.

Table 2: Validating Close Tie as a measure of Network Strength

	Multinomial Logit (MNL) Marginal Effects[1] (at means of independent variables)			(log) Wage Regression[4] (low wage imputed to the never employed)	
	Formal Job[2]	Network Job[2]	Never Employed	50th Percentile	75th Percentile
	(1)	(2)	(3)	(4)	(5)
Close Tie	-0.045***	0.086***	-0.041	0.096	0.086**
	[0.018]	[0.023]	[0.026]	[0.089]	[0.036]
Observations		6374		5964	5964
Clusters[3]		545		427	427

*** p<0.01, ** p<0.05, * p<0.10 using two-tailed tests

[1]Full specification includes the 'Explanatory Variables' described in table 1, metropolitan dummies and country of birth dummies. Robust standard errors, clustered at the metropolitan-country of birth level, are shown within brackets.

[2]Refers to the *first* job.

[3]Refers to metropolitan-country of birth groups

[4]Full specification consists of all variables used in the MNL. Standard errors are obtained using clustered bootstrap where replications are based on metropolitan-country of birth clusters.

Table 3: Network Premium and Close Tie
(Log) Wage Regression (conditional on being employed)

	OLS[1]	Quantile Regressions at various deciles[2]								
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Close Tie	0.096*	0.256**	0.241***	0.102	0.090*	0.083**	0.049	0.035	0.076	-0.016
	[0.052]	[0.127]	[0.086]	[0.084]	[0.048]	[0.041]	[0.037]	[0.043]	[0.058]	[0.086]
Network Job	0.052	0.329*	0.264**	0.139	0.107*	0.040	-0.026	-0.040	-0.016	-0.204**
	[0.076]	[0.171]	[0.118]	[0.101]	[0.058]	[0.051]	[0.050]	[0.071]	[0.072]	[0.089]
Network Job*Close Tie	-0.090	-0.287	-0.252**	-0.142	-0.112*	-0.060	-0.004	0.001	-0.066	0.072
	[0.085]	[0.198]	[0.126]	[0.103]	[0.059]	[0.051]	[0.049]	[0.072]	[0.080]	[0.090]
Observations	4094	4094	4094	4094	4094	4094	4094	4094	4094	4094

*** $p<0.01$, ** $p<0.05$, * $p<0.10$ using two-tailed tests. Full specification includes the ‘Explanatory Variables’ described in table 1, metropolitan dummies and country of birth dummies.

[1]Standard errors clustered at metropolitan-country of birth level, R squared is 0.18

[2]Standard errors are obtained using clustered bootstrap where replications are based on 358 metropolitan-country of birth clusters.

Table 4: Difference in Differences for Observed Characteristics

	OLS								Ordered Logistic Coefficients
	Female	Age	Married	No. of children	Speaks English	Speaks French	Lived in Can. Before	Principal Applicant	Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Close Tie	0.015	0.359	0.018	0.027	0.077*	-0.013	0.003	0.072**	-0.260**
	[0.028]	[0.545]	[0.027]	[0.065]	[0.043]	[0.037]	[0.012]	[0.036]	[0.108]
Network Job	0.081	0.596	0.016	0.106	-0.128**	-0.036	-0.016	-0.075	-0.490***
	[0.059]	[1.024]	[0.039]	[0.079]	[0.049]	[0.053]	[0.021]	[0.046]	[0.166]
Network Job*Close Tie	-0.069	-0.376	-0.030	-0.041	-0.053	-0.008	-0.007	0.029	-0.441**
	[0.065]	[0.870]	[0.040]	[0.088]	[0.046]	[0.048]	[0.022]	[0.049]	[0.204]
Observations	4094	4094	4094	4094	4094	4094	4094	4094	4094
R-squared	0.007	0.003	0.003	0.001	0.035	0.006	0.003	0.005	
Log Pseudolikelihood									-90111.573

*** p<0.01, ** p<0.05, * p<0.10 using two-tailed tests; Robust standard errors in brackets, clustered at the metropolitan-country of birth level (358 clusters).

Table 5: Skill Bias Check: (Log) Wage Regression (conditional on being employed)

	OLS[2]		Quantile Regression, third decile[3]	
	All Controls[1]	Excluding Observed Skills	All Controls[1]	Excluding Observed Skills
	(1)	(2)	(3)	(4)
Close Tie	0.096*	0.093*	0.241***	0.264***
	[0.052]	[0.052]	[0.086]	[0.099]
Network Job	0.052	0.039	0.264**	0.226*
	[0.076]	[0.073]	[0.118]	[0.126]
Network Job*Close Tie	-0.090	-0.100	-0.252**	-0.214
	[0.085]	[0.085]	[0.126]	[0.134]
Language skills	Yes	No	Yes	No
Visa category	Yes	No	Yes	No
Occupation before migrating	Yes	No	Yes	No
Education level	Yes	No	Yes	No
R-squared	0.18	0.16		
Clusters	358	358	358	358
Observations	4094	4094	4094	4094

*** $p<0.01$, ** $p<0.05$, * $p<0.10$ using two-tailed tests. Unless specified, full specification includes
[1]'All Controls' includes the 'Explanatory Variables' described in table 1, metropolitan dummies and country of birth dummies.
[2]Standard errors clustered at metropolitan-country of birth level
[3]Standard errors are obtained using clustered bootstrap where replications are based on metropolitan-country of birth clusters.

Table 6: Structural Parameter Estimates of Offer Probabilities and (Log) Wage-Offer Distributions

	Source Specific Offer Distributions[1] (1)	Identical Network Offer Distributions[2] (2)	Single Offer Distribution[3] (3)
Probability formal offer	0.47	0.47	0.47
	(0.01)	(0.01)	(0.01)
Probability network offer (strong)	0.45	0.45	0.45
	(0.01)	(0.01)	(0.01)
Probability network offer (weak)	0.25	0.24	0.24
	(0.02)	(0.02)	(0.02)
Mean formal offer distribution	5.25	5.25	5.26
	(0.20)	(0.20)	(0.20)
Std. dev. formal offer distribution	0.67	0.67	0.63
	(0.01)	(0.01)	(0.01)
Mean network offer distribution (strong)	5.25	5.24	Not Applicable
	(0.20)	(0.20)	
Std. dev. network offer distribution (strong)	0.57	0.57	Not Applicable
	(0.01)	(0.01)	
Mean network offer distribution (weak)	5.17	Not Applicable	Not Applicable
	(0.20)		
Std. dev. network offer distribution (weak)	0.62	Not Applicable	Not Applicable
	(0.04)		
Log-likelihood	-10296.47	-10298	-10324.02

Standard errors in parentheses.
[1]Each source allowed to have its own specific offer distribution
[2]Offer distributions from weak networks and strong networks constrained to be identical
[3]All offer distributions constrained to be identical