

# Social Ties and the Job Search of Recent Immigrants<sup>\*†</sup>

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## Abstract

We show that the wage differential in first jobs between those accepting an offer from their network and those accepting one from formal channels *decreases* with the likelihood of a network offer. This is a counterintuitive result and using a theoretical model we provide the rationale for it. We also verify this result empirically for recent immigrants to Canada. We show that for these immigrants the likelihood of a network offer is captured by the presence of a ‘close social tie’. Furthermore, a structural model confirms 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 this offer is drawn.

Key words: Job Search, Migration, Networks

JEL Codes: J3

# 1 Introduction

In the economics literature on social networks there is disagreement about whether networks as represented by immigrant enclaves provide access to higher paying jobs ((Munshi 2003); (Edin, Fredriksson, and Aslund 2003)) or to less desirable ones ((Borjas 2000); (Chiswick and Miller 2005)). In this paper we model networks as increasing access to job offers and allow offers from networks to be better or worse than those from formal (non-network or impersonal) channels. Using a theoretical model we show a counterintuitive result, namely that the wage differential in first jobs between those accepting a job offer from their network and those accepting one from formal channels *decreases* as the likelihood of a network offer increases. We verify this result empirically using data on recent immigrants to Canada.

Drawing on Montgomery (1992), we model the first period of a multi-period job search process. We characterize the strength of a network by its likelihood of providing a job offer rather than by its wage-offer distribution. We hypothesize that a stronger network is more likely to yield an offer. We derive the counterintuitive implication that the observed difference in wages in the first job between those who have accepted an offer from their network and those who have accepted one from the formal channels, will be more negative (or less positive) when the network is stronger. In other words, our model implies that the network wage premium decreases in network strength.

We use a nationally representative survey of very recent immigrants to Canada to test this implication. We use the presence or absence of at least one ‘close social tie’ in Canada as our measure of network strength. Employing a difference-in-differences approach we confirm this and other related implications in the data.

Finally, to test the relevance of our characterization of the strength of a network, we estimate a structural model that allows us to uncover the underlying network and formal wage-offer distributions and offer probabilities. The structural parameter estimates provide further support for our conclusion that, for recent immigrants to Canada, a stronger social network, characterized by the presence of a close social tie, operates by increasing the likelihood of generating an offer from the network

rather than by altering the distribution from which this offer is drawn.

We make three contributions to the literature on how social networks influence labor market outcomes. First, we simplify and extend Montgomery's (1992) model of the role of social networks in job search. We simplify it by assuming that workers obtain at most one offer from each job source but drop Montgomery's assumption of identical network and formal wage-offer distributions. We show that, conditional on being employed, the wage difference in first jobs between those who accepted a network offer and those who accepted a formal offer decreases in network strength. This result holds, both, at the mean and at almost all percentiles of the observed network and formal wage distributions. That the network wage premium decreases in network strength even when we allow the offer distributions to differ, and that this result holds at most percentiles, are novel contributions of this paper.

Second, our paper is the first attempt to confront Montgomery's model with data. Given our focus on studying the role of networks for new entrants in the labour market, in the empirical section we consider a cohort of very recent immigrants who do not have pre-arranged jobs and have been in the host country for only about six months. We examine the influence of their network on their first job after arrival.

Third, most empirical studies of the effect of social networks on immigrants' labor market outcomes focus on "network size," typically captured by the number of other immigrants from the immigrant's own country. The best studies use instrumental variables (Munshi 2003) and quasi-experiments ((Edin, Fredriksson, and Aslund 2003); (Damm 2009); (Beaman 2012)) to address the potential endogeneity of network size, but reach conflicting conclusions about its effects. Moreover, they do not describe the mechanism through which network size affects labor market outcomes. This paper takes a different approach. We capture an immigrant's social network by the presence of a close social tie. A close social tie is defined to be a relative or friend already living in the host country when the immigrant had just arrived. Our data allow us to use this uncommon, but intuitively appealing, measure of an immigrant's social network.<sup>1</sup> We hypothesize that the presence of at least one

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<sup>1</sup>In Goel and Lang (2009), we experimented with using 'network size' as another measure of network strength. However, network size did not satisfy the pre-conditions required of a valid mea-

close social tie in the host country improves the strength of an immigrant’s network in the sense that his network is more likely to generate a job offer. Our empirical strategy is based on a standard difference-in-differences assumption.

The rest of 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 heavily on Montgomery (1992). He examines the case of a worker who simultaneously uses two sources of wage-offers in searching for a job. For consistency with the terminology of this paper, we refer to these sources as “the worker’s network” and “formal channels.” Montgomery considers the case where these 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 the formal channels.

This initially counter-intuitive result that the mean wage is *lower* in jobs found through the *stronger* source (the stronger source being the one providing a higher average number of offers), is actually quite intuitive. Montgomery explains the intuition with the following extreme example. Suppose the formal channels almost never generate an offer, while the network almost always yields an offer. In this scenario, almost all workers receive an offer from the network, while very few also receive one from the formal channels. Therefore, *ex post*, those who accepted an offer from formal channels almost definitely chose the best of *two* offers, while those

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sure of network strength. These pre-conditions are explained later (see section 3). We, therefore, do not discuss network size in this version.

who accepted an offer from the network almost all chose the *one* offer they had. Therefore, on average, even though the network is stronger than the formal channels, those in jobs found through the formal channels have higher wages compared to those in jobs found through the network.

We simplify Montgomery's model by limiting the number of possible 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 about six months, this assumption may not be unduly restrictive. Few will have received multiple offers through a single mechanism.<sup>2</sup> Further, we extend Montgomery's model to allow the sources to have *different* wage-offer distributions. Our extension is important because there are many reasons for the network and formal offer distributions to differ. Montgomery (1991) argues that workers who are referred to the employer through their network are better, on average, than those who apply directly. Similarly, Dustmann, Glitz, and Schoenberg (2011) argue that the network improves the ability of employers to recognize the workers with the highest match-specific productivity. On the other hand, networks might be more useful for finding jobs at smaller firms with less formal application and evaluation policies, and that pay lower wages. Bentolila, Michelacci, and Suarez (2010) argue that worker-job matches tend to be poorer for jobs found through the network. In our model, we are indifferent about which source provides better offers and allow for either possibility.

We now describe our model in detail. Consider a new job market entrant who is looking for a job. We adopt a discrete time set up because some subset of new entrants receive two competing offers before accepting a job. Search is therefore nonsequential. More realistically, there is a time gap between receiving an offer and accepting it, but modeling a continuous time model with job offers that have discrete periods before they expire is unduly complicated. We focus on the first period following entry.

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<sup>2</sup>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.

We assume that all entrants have the same value of leisure, which, without loss of generality, we normalize to zero. Wages can then be interpreted as the difference between the nominal wage and the value of leisure. As in Burdett and Mortensen (1998), offers rain down upon workers at a constant rate regardless of whether they are employed or unemployed. Consequently, an unemployed worker's reservation wage is his value of leisure (normalized to zero). If he receives more than one offer, he chooses the one with the highest wage.

Suppose he has two sources of wage-offers, his network and formal channels. Assume that he can receive at most one offer from each source. With probability  $p_n$  he receives an offer from his network, and with probability  $p_f$  he receives one from formal channels.  $p_n$  is defined to be the strength of his network. The higher the value of  $p_n$ , the stronger is his network. Denote the distribution of wages from which the network offer is drawn as  $F_n(w)$ . Similarly, denote the distribution of the formal wage-offers as  $F_f(w)$ , where  $F_n(w)$  and  $F_f(w)$  are defined over the positive real line.<sup>3</sup> 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 unemployment, a higher probability of either type of offer must make workers better off, an auxiliary prediction that we confirm in the results section.

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<sup>3</sup>There is no loss of generality from ignoring negative wage offers that all workers would reject.

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,

$$E(w|f) = \frac{(1 - p_n)E(w_f) + p_n \Pr(w_f > w_n)E(w_f|w_f > w_n)}{(1 - p_n) + p_n \Pr(w_f > w_n)} \quad (3)$$

This is increasing in network strength,  $p_n$ . It follows that the difference between the mean wage 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,  $p_n$ .

**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,

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

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

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  $\omega_1$  and  $\omega_2$ , 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 simulation to get a sense of where the effect of network strength is likely to be the largest. For simulation, 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 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 always 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.<sup>4</sup>

## 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:

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.

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<sup>4</sup>More detailed results from these preliminary simulations can be made available on request.

### 2.3 Empirical tests of the Theory: Threats by Other Network Mechanisms

In our model, network strength has been characterized by the probability of receiving an offer from the network. In other words, we believe that a stronger network influences observed wages by increasing the probability of generating a network offer. However, there are other ways to characterize network strength. For example, it could be characterized by an improvement in the network wage-offer distribution. 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. We are primarily concerned about incorrectly accepting our theory about how networks operate. Although we discuss scenarios where we might fail to find empirical support for our model in spite of our mechanism being operative, this is not our main focus as we are more concerned about falsely accepting our theory rather than falsely rejecting it.

As mentioned in the introduction, our empirical measure of network strength is the presence of a close social tie in the host country. Keeping this measure in mind 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 offers from the network, the possibility of sequential search, and worker heterogeneity.

First consider potential effects of a close tie on wage-offer distributions. One possibility is that a close tie does not change the formal offer distribution, but worsens the network offer distribution: for example, if social norms dictate that the new immigrant should work for his cousin, then his cousin may exploit the situation and offer him a low wage. In this case, our prediction that the network premium is decreasing in network strength would be confirmed, but for a reason that is different from the one described in our model. However, note that the observed network wage distribution would be worsening in network strength, which would contradict

prediction 1 above that the observed network distribution is independent of network strength. We can check this in our data and when we do so (section 5.3.1) we find no evidence in its support. Another possibility is that a close tie provides access to high-wage formal jobs, i.e. it 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. Again, we will check and fail to confirm this.

Second, consider the possible effect of a close tie on the offer probability from formal channels. Workers with a close tie might endogenously reduce effort in their search through formal channels. This would reduce the probability of receiving a formal offer. This would in turn reinforce our prediction that the network premium is decreasing in network strength. Since this is an endogenous response to the mechanism we identify, we do not consider it to be problematic. On the other hand, if a close tie works only by increasing the probability of a formal offer (and does not affect the probability of a network offer), then we would not find empirical support for our prediction. We would then correctly reject our theory.

Yet another possibility arises if we allow for multiple network offers: a close tie increases the probability of receiving a greater number of offers from the network. This would result in an improvement in the effective network offer distribution. This is because it would be the first-order statistic of the multiple network offers. At the same time, the distribution of accepted formal offers is still increasing in network strength. This is because of 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 as in our model (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” of our model.

Another concern is that, like Burdett and Mortensen (1998), we do not allow

the arrival rate of offers to depend on employment status. If it did, then workers' reservation wages when unemployed would be sensitive to the arrival rate of offers both when employed and unemployed. 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. **Alternatively, search could be sequential rather than non-sequential as we have assumed.** Again, changes in the arrival rate of offers would change the reservation wage. If the offer distributions from the two sectors are similar, which our estimates, shown later, suggest they are, changes in the reservation wage should not greatly affect our predictions.

Finally, in our model we have considered a group of homogeneous labour market entrants, whereas we will be testing the model on a set of heterogeneous immigrants. This raises two issues. The first is that the presence of a close tie might be associated with a difference in the wage differential between immigrants in network and formal jobs for exogenous reasons i.e. those that are unrelated to an increase in the probability of a network offer. If, for example, the presence of a close tie only helps high-skill immigrants find jobs through formal channels, then there would be a less positive (or more negative) network-formal skill differential in the presence of a close tie, and this would lead us to falsely accept our model. It appears to us that all such mechanisms would imply that both network and formal wages are affected by network strength, which we can, again, check in our data. The second issue, which in our view is not problematic, 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 almost surely increases 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 reinforce our prediction that the network premium is decreasing in network strength. It is important to note that this is not problematic as it 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  $CT = 0$ .<sup>5</sup> 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. Keeping this in mind, network strength should 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 work-

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<sup>5</sup>The two survey questions used to construct the *close tie* variable are as follows: 1) When you arrived in Canada did you have relatives already living here? 2) When you arrived, in Canada did you have friends (who were not relatives) already living here in Canada? The answers to these questions could be either a ‘Yes’ or a ‘No’. If the respondent answered in the affirmative to at least one question, then  $CT = 1$ , otherwise  $CT = 0$ .

ers 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,

$$\ln \frac{P_{ijk}^l}{P_{ijk}^u} = \delta_0^l + \delta_1^l CT_{ijk} + \delta_2^l X_{ijk} + \omega_j^{1l} + \lambda_k^{1l} \quad (4)$$

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  $\omega_j^1$  and  $\lambda_k^1$  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,

$$\ln w'_{ijk} = \alpha_0 + \alpha_1 CT_{ijk} + \alpha_2 X_{ijk} + \omega_j^2 + \lambda_k^2 + v_{ijk}. \quad (5)$$

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 (4) above. For  $CT$  to be a valid measure of network strength,  $\alpha_1$  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 (5), 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,

$$\ln w_{ijk} = \theta_0 + \theta_1 CT_{ijk} + \theta_2 NJ_{ijk} + \theta_3 (NJ_{ijk} * CT_{ijk}) + \theta_4 X_{ijk} + \omega_j^3 + \lambda_k^3 + \zeta_{ijk} \quad (6)$$

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.

$\theta_1$  might be positive for reasons unrelated to a higher probability of receiving a network offer. If, for example, immigrants with a close tie are different from those without one, then  $\theta_1$  could be spuriously positive (negative) if those with a close tie are more positively (negatively) selected than those without a close tie. 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,  $\theta_3 < 0$ . It is important to understand what we are attempting to measure. It is the causal effect of increasing network strength on the *equilibrium wage difference* between workers who chose to accept a job found through their network and those who chose to accept one found through the formal channels. It is *not* the causal effect of network strength on the wage

difference between workers randomly assigned to jobs obtained through each of the two sources. For a consistent estimate of  $\theta_3$ , 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:

$$E(\zeta_{ijk} | NJ_{ijk} = 1, CT_{ijk} = 1, Z_{ijk}) - E(\zeta_{ijk} | NJ_{ijk} = 1, CT_{ijk} = 0, Z_{ijk}) = \\ E(\zeta_{ijk} | NJ_{ijk} = 0, CT_{ijk} = 1, Z_{ijk}) - E(\zeta_{ijk} | NJ_{ijk} = 0, CT_{ijk} = 0, Z_{ijk}) \quad (7)$$

where

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

A comparison with a well-known difference-in-differences study may help to clarify equation (7). Gruber and Poterba (1994) examine the effect on health insurance (HI) coverage of giving favorable tax treatment to HI purchases by the self-employed. The authors compare HI coverage of the self-employed and regular employees before and after the tax change. There are two ways that the tax change could change HI coverage of the self-employed relative to the regular employed. First, by reducing the after-tax price of health insurance, it encourages the self-employed to purchase health insurance. Second, by changing the relative price of HI in the two sectors, it changes the compensating differential for self-employment versus regular employment, and possibly shifts some workers who would buy HI in either sector from regular employment to self-employment. This is an endogenous shift in sectoral composition caused by the tax change. If we want to measure the effect of tax change on HI coverage of a particular set of self-employed workers, we require that the worker-reallocation effect be negligible. Instead, if we want to examine the equilibrium difference in coverage rates between the self-employed and the regular employed that can be attributed to the tax change, then this endogenous shift in sectoral composition is not problematic and the difference in coverage rates due to a change in sectoral composition should also be included as part of the effect

of the tax change. However, if there were a shift in sectoral composition for reasons unrelated to the tax change (i.e. an exogenous shift), it would need to be accounted for in order to measure the true effect of the tax change.

Our case is somewhere in between. 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 who arrived in Canada between October 1, 2000 and September 30, 2001, and were 15 years or older. It is a longitudinal survey with three waves: immigrants are interviewed at six months, two years and four years since arrival in Canada. 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; **who are be-**

**tween 15 and 64 years old (working age population);** who are in the labor force; and who live in metropolitan areas in Canada.<sup>6</sup> We exclude immigrants who were in prearranged jobs,<sup>7</sup> or self employed, or in family businesses.<sup>8</sup> Finally, we limit the analysis to immigrants from metropolitan areas and from source countries with at least ten immigrants in the LSIC sample.<sup>9</sup> 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 uses the LSIC estimation sample to arrive at summary statistics for recent immigrants at six months after arrival. Column (1) presents 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. 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

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<sup>6</sup>A census metropolitan area (CMA), or a census agglomeration (CA), is formed by one or more adjacent municipalities centered on a large 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 will be collectively referred to as metropolitan areas.

<sup>7</sup>When asked about their first jobs, 7.2 percent of the recent immigrants report being in pre-arranged 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, we find that immigrants with prearranged jobs are distinct 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. On the other hand, they 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.

<sup>8</sup>2.1 percent reported being self-employed, and 0.6 percent reported being in family businesses.

<sup>9</sup>Experimentation showed that trying to reduce this cutoff of ten, resulted in very large standard errors in our quantile regressions that contain country of birth and metropolitan fixed effects. We lose 5.9 percent of the remaining LSIC sample due to this restriction. 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.

the employer directly, responding to newspaper advertisements, employment agencies, the internet and referral from another employer or a union.<sup>10</sup> 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, conditional on being employed, 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.<sup>11</sup>

Two things must be noted at this point. First, reporting the first job to be a network job ( $NJ = 1$ ) does not imply the presence of a close tie ( $CT = 1$ ), and vice versa. This is because an immigrant may not have had a close tie and even then he could have found the network job through a friend made *after* migrating to Canada or through a relative or friend *not* living in Canada. Similarly, reporting the presence of a close tie does not imply that his first job is a network job. Even in the presence of a close tie, he may have found his first job through formal channels or he may have remained unemployed. Second, to the extent that job search is complex, the dichotomous measure of the 'use of the social network' captured by the binary variable  $NJ$ , and the theoretical concept it wishes to encapsulate, are not

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<sup>10</sup>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 of these nine questions could be either a 'Yes' or a 'No'. 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 in the affirmative, then  $NJ = 1$ .  $NJ = 0$  otherwise.

<sup>11</sup>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.

perfectly related. For example, consider that a friend tells me about a job opening where he works, 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 ( $NJ = 0$ ), or both? Thus, admittedly, our measure of *use of network* is imperfect. However, in contrast with much recent research (e.g. (Bayer, Ross, and Topa 2008); (Hellerstein, McInerney, and Neumark 2011); (Dustmann, Glitz, and Schoenberg 2011)), we measure network use directly and therefore avoid the need to infer network use from the clustering of immigrants, though we may miss some of the network use that their indirect measure can capture.

## 5 Results

We present our empirical findings by first providing evidence to support the use of close tie as a valid measure of network strength. Next, report coefficient 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 also explain our findings. Finally, we present structural estimation results to provide further support for the mechanism through which the close tie measure operates.

### 5.1 Validating Close Tie

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 (4)), 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 (5)). 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.<sup>12</sup> 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 (6): 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

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<sup>12</sup>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 (5) 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).

between these two variables.<sup>13</sup> 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. 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

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<sup>13</sup>When interpreting the coefficients on close tie, network job and their interaction, it should be noted that the omitted group is that of recent immigrants in formal jobs and without a close tie.



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.<sup>14</sup>

### 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,

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<sup>14</sup>We examined, at the second decile, the interaction term separately for men, women; high education, low education; 30 and younger and over 30. In all cases the coefficient on the interaction term was negative, but bootstrapping the standard errors was unreliable because of the small sample sizes.

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 (6) is regressed on close tie, network job and 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 nevertheless a 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 (6). 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.<sup>15</sup> In particular, while controlling for skill

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<sup>15</sup>Also, for the regression at the second decile excluding observed skills, although the interaction

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 in the appropriate way, the fact that, excluding this extensive set 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 the same network wage-offer distribution 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 social 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.

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term is not significant at conventional levels, the p value is 0.110.

## 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,  $\omega$ , is drawn from a source specific offer distribution given by

$$\omega_{ij} = X_i\beta + \alpha_j + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma_j^2) \quad (8)$$

where  $i$  denotes the immigrant and  $j$  denotes the source (formal channels  $f$ , strong network  $s$ , and weak network  $w$ ). Thus,  $\alpha_j$  is a source-specific factor shifting the mean of the offer distribution. Also, we allow the variance of the error,  $\sigma_j^2$ , 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,

$$LF(u|CT = 1) = (1 - p_f)(1 - p_s) \quad (9)$$

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

$$LF(u|CT = 0) = (1 - p_f)(1 - p_w) \quad (10)$$

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

$$LF(\omega, NJ = 1|CT = 1) = \left[ p_s \left\{ (1 - p_f) + p_f \Phi \left( \frac{\alpha_s - \alpha_f + \varepsilon_{is}}{\sigma_f} \right) \right\} \right] \phi_s(\varepsilon_{is}) \quad (11)$$

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  $\Phi$  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  $\Phi$  is the probability that

$$X_i\beta + \alpha_f + \varepsilon_{if} < X_i\beta + \alpha_s + \varepsilon_{is} \quad (12)$$

or

$$\Pr\left(\frac{\varepsilon_{if}}{\sigma_f} < \frac{\alpha_s - \alpha_f + \varepsilon_{is}}{\sigma_f} \mid \varepsilon_{is}\right) \text{ where } \frac{\varepsilon_{if}}{\sigma_f} \sim N(0, 1) \quad (13)$$

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 ( $\alpha_j, \sigma_j$ )

## 6.2 Results from Structural Estimation

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.<sup>16</sup>

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<sup>16</sup>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

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 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 social 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 prob-

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distributions.

abilities. The results are mixed.<sup>17</sup> 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 power to detect this effect.

## 7 Summary and Conclusions

In this paper, we develop a theoretical model that draws heavily on (Montgomery 1992). Our model describes the importance of social networks for recent immigrants seeking jobs. It defines the strength of an immigrant’s network by the likelihood with which it provides a job offer. Considering that an immigrant can find a job either through his social network or through the formal (non-network) channels, our model implies that the network wage premium (network-formal wage differential) is decreasing in network strength.

We test this implication on a nationally representative sample of recent immigrants to Canada. We show that 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 confirm the prediction that the network premium decreases with network strength. Evidence in favor of our model is especially strong at the lower end of the observed wage distribution (first four deciles), the region where initial simulations had lead us to anticipate finding the largest effects. This suggests that, for a recent immigrant, the presence of a close social tie in the host country increases the probability of receiving an offer from his network.

To further test our conclusion, we estimate a simple structural version of the model. The estimates support the conclusion that the primary role of a close social

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<sup>17</sup>Simulation results available on request.

tie is to increase the probability of generating a wage offer from the network rather than to alter the distribution from which this offer is drawn. These estimates also suggest that the network and formal offer distributions differ only modestly, so that Montgomery's (1992) model can 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 in the economic assimilation of recent immigrants. The mechanism through which such social networks operate is that when recent immigrants are looking for jobs, they receive a larger number of offers from which to choose. Our analysis also suggests that such close social ties do not influence the kind of job offers that immigrants receive since offers obtained through formal channels and networks are similar. In other words, in the absence of close social ties, recent immigrants would receive fewer offers, but the individual offers they do receive are 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 immigrant social networks.



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

	All Recent Immigrants		Without Close Tie	With Close Tie
	Mean (Std. Dev.)	Sample Size		
	(1)	(2)	(3)	(4)
<i>Network Strength Measure</i>				
Close Tie (CT)	0.89	6524		
<i>Job Outcomes</i>				
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)
<i>Explanatory Variables</i>				
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
<i>Education</i>				
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
<i>Visa Category</i>				
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
<i>Occupation before migrating</i>				
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

Variation in the Sample Size (column 2) is due to variation in missing data across variables. In case of the Weekly Wage variable, those who were never employed within the first six months have missing values. LSIC sample has been appropriately weighted to reflect statistics for the target population.

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

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

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

<sup>1</sup>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.

<sup>2</sup>Refers to the *first* job.

<sup>3</sup>Refers to metropolitan-country of birth groups

<sup>4</sup>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)

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

<sup>1</sup>Standard errors clustered at metropolitan-country of birth level, R squared is 0.18

<sup>2</sup>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									
	Female	Age	Married	No. of children	Speaks English	Speaks French	Lived in Can. Before	Principal Applicant	Ordered Logistic Coefficients Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Close Tie	0.015 [0.028]	0.359 [0.545]	0.018 [0.027]	0.027 [0.065]	0.077* [0.043]	-0.013 [0.037]	0.003 [0.012]	0.072** [0.036]	-0.260** [0.108]
Network Job	0.081 [0.059]	0.596 [1.024]	0.016 [0.039]	0.106 [0.079]	-0.128** [0.049]	-0.036 [0.053]	-0.016 [0.021]	-0.075 [0.046]	-0.490** [0.166]
Network Job*Close Tie	-0.069 [0.065]	-0.376 [0.870]	-0.030 [0.040]	-0.041 [0.088]	-0.053 [0.046]	-0.008 [0.048]	-0.007 [0.022]	0.029 [0.049]	-0.441** [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 <sup>2</sup>		Quantile Regression, third decile <sup>3</sup>	
	All Controls <sup>1</sup>	Excluding Observed Skills	All Controls <sup>1</sup>	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  
<sup>1</sup>'All Controls' includes the 'Explanatory Variables' described in table 1, metropolitan dummies and country of birth dummies.

<sup>2</sup>Standard errors clustered at metropolitan-country of birth level

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

Standard errors in parentheses.

<sup>1</sup>Each source allowed to have its own specific offer distribution

<sup>2</sup>Offer distributions from weak networks and strong networks constrained to be identical

<sup>3</sup>All offer distributions constrained to be identical