CDE
September 2010

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Working Paper No. 189

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Social Ties and the Job Search of Recent Immigrants*†

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Abstract

We show that increasing the probability of obtaining a job offer through the network should raise the observed mean wage in jobs found through formal (non-network) channels relative to that in jobs found through the network. This prediction also holds at all percentiles of the observed wage distribution, except the highest and lowest. The largest changes are likely to occur below the median. We test and confirm these implications using a survey of recent immigrants to Canada. We also develop a simple structural model, consistent with the theoretical model, and show that it can replicate the broad patterns in the data. For recent immigrants, our results are consistent with the primary effect of strong networks being to increase the arrival rate of offers rather than to alter the distribution from which offers are drawn.

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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, Singapore Management University, Universitat Autonoma de Barcelona and University College London 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

While it is plausible that networks play an important role in the labor market assimilation of immigrants, there is mixed evidence about this in existing literature ((Lazear 1999); (Bertrand, Luttmer, and Mullainathan 2000); (Munshi 2003); (Edin, Fredriksson, and Aslund 2003)). Also, little is known about the mechanisms through which networks affect the labor market outcomes of recent immigrants. In this paper we attempt to fill this gap. We develop a theoretical model of the role of networks, and, using survey data on recent immigrants into Canada, we test our model's comparative static properties. We also estimate a simple structural version of the model. Our results are consistent with the principal effect of strong networks being to increase the arrival rate of offers rather than to change the distribution from which offers are drawn.

Our theoretical model builds on Montgomery (1992), who shows that when networks and formal (non-network) channels draw on the same wage-offer distributions, among workers whose networks are *stronger* than formal channels (in the sense that each worker's network has a greater probability of providing job offers than do formal channels), those who accept a job offered through the network should, on average, have *lower* wages than those who accept one offered through formal channels. We simplify his model by assuming that workers can obtain at most one job offer from each source, and then extend it to allow the two sources to have different offer distributions. We show that the expected wage conditional on having accepted a job offered through formal channels is increasing in network strength (the network's probability of providing a job offer), while the expected wage conditional on having accepted a job offered through the network is unaffected by network strength. It follows that the mean wage differential between those who accept network jobs and those who accept formal jobs is decreasing in network strength. Moreover, these predictions hold at all percentiles of the observed wage distribution except the highest and lowest. We provide an intuitive argument that the effect is likely to be largest (in absolute terms) at percentiles below the median of the observed wage distribution.[1]

In the empirical section we consider two potential measures of a recent immigrant's network strength. The first is "network size". It is captured by the (log) share of the working-age population in the immigrant's area of residence that is from his country of origin and has been in Canada for at least five years. This is the measure of network strength most commonly used in the economics literature. There are many reasons why network size may be important in job search. Employers within an enclave may prefer to hire individuals from their own country (Borjas 2000), but living in an enclave may also lower the speed with which new immigrants learn host country skills, e.g. language (Lazear 1999), and this may lower the quality of job offers they receive. Further, whether new immigrants benefit from such segregation may depend on the quality of the enclave, e.g. the stock of human capital, ((Edin, Fredriksson, and Aslund 2003); (Borjas 1992); (Borjas 1995)).

The causal effect of enclaves, or networks more generally, is difficult to determine because of the likelihood of omitted variables bias. There may be important unmeasured factors that make immigrants from a particular country more suitable for jobs concentrated in particular locations, and/or unobserved differences between individuals who choose to locate near other members of

[1] There is a growing theoretical literature on the role of networks in job finding which we do not attempt to survey here. We refer the reader to chapter 9 of Zenou (2009).

their ethnic group and those who do not. Munshi (2003), Edin, Fredriksson, and Aslund (2003) and Beaman (2009) use instrumental variable techniques to address this concern and find positive effects of network size, at least as measured by number of established immigrants, but do not address the mechanism that generates these positive effects. In this paper we attempt to do this.

The second measure of network strength is "close ties." This is closely related to the sociological concept of strong ties and refers to whether the new immigrant had at least one relative or friend in Canada when he first arrived. In very different contexts from the one we study, Granovetter (1973) finds that, relative to strong ties, weak ties (acquaintances as opposed to relatives or friends) increase the arrival rate of job offers, and Lin, Vaughn, and Ensel (1981) argue that weak ties provide links to better jobs. Here we consider the possibility that close ties increase the probability of getting an offer through the worker's network. Consistent with our model in which the effect on observed wages depends on the relative probability of finding a job through the network or formal channels and is therefore likely to be time and location specific, the literature finds mixed results on the relation between wages and job-finding method.[2]

If the distinction between a strong and weak network is the arrival rate of job offers through the network, then immigrants with stronger networks should be more likely to be working in jobs they found through the network, and they should be less likely to be working in jobs they found through formal mechanisms or to be unemployed. Also, if we treat being unemployed as having a very low wage, the distribution of wages among those with strong networks should be better than that of those with weak networks, in the sense of first-order stochastic dominance. Before examining the principal predictions of our model, we pretest our measures of network strength to determine whether they satisfy these conditions. We find that having close ties is associated with a greater probability of finding a job through the network, a lower probability of finding a job through formal channels and a somewhat lower probability of unemployment. It is also associated with higher wages. In contrast, having a larger network size is associated with a higher probability of finding a job through the network, but not with a lower probability of finding a job through formal means. It is also not associated with higher wages. We therefore conclude that whatever is captured by network size, it is not solely a measure of network strength. Either network size affects labor market outcomes in ways not captured by our theory, or other differences between workers with larger and smaller networks are sufficient to obscure the role of network size as a measure of network strength. Consequently, for the remainder of the paper, our focus is on close ties as the measure of network strength.

The main testable implication of our theoretical model is that the network premium (the mean wage differential between those who accept network jobs and those who accept formal jobs) is decreasing in network strength (the network's probability of providing a job offer). We test this by examining the interaction between network strength (captured by the presence of close ties) and the method (network or formal) the immigrant used to find his first job, if any, within six months of arriving in Canada. At the first quartile of the observed wage distribution, for those without close ties, finding a job through the network is associated with higher wages compared to finding one through formal methods. Also, as predicted by the model, for those in formal jobs, the presence of close ties is associated with higher wages, while for those in network jobs, the presence of close

[2] See for example (Kugler 2003); (Marmaros and Sacerdote 2002); (Patel and Vella 2007) and (Pellizzari 2004).

ties does not have a statistically significant effect on wages. More importantly, the interaction between close ties and finding a job through the network is negative, confirming that the network premium is indeed decreasing in network strength. We observe a similar pattern for the interaction term at the median and 75th percentile and for mean wages, however, the coefficient estimates fall short of significance at conventional levels.

Based on our theoretical model and simulations, we anticipated that the coefficient on the interaction term would be larger at lower quantiles, so these findings are consistent with our predictions. However, this does not address directly the question of whether network strength simply increases the arrival rate of offers or also changes the offer distribution. To address this, we estimate a simple structural model in which wages are drawn from different log normal distributions that vary by source (network or formal) and by network strength, and in which we also allow for different probabilities of receiving offers. The estimates of the structural model imply that the primary role of networks is to increase the flow of job offers rather than to change the wage distribution from which offers are drawn.

In section 2 we develop the theoretical model of networks and derive its implications. Section 3 describes the empirical framework. In section 4 we provide a brief description of the data. The main empirical results are presented in section 5. Section 6 presents the structural model, and section 7 concludes.

2 Theoretical Model

Our model draws heavily on Montgomery (1992). For the case where network and formal methods of job search draw on the same offer distributions, the result regarding the expected wage conditional on job-finding method can be found there in more general form by translating variables appropriately. We simplify his model, and extend it to allow for different offer distributions.

Consider a single period model in which a representative recent immigrant is looking for jobs. He faces two sources of job offers, the network source, and the formal (non-network) source. For example, he can search for jobs as an academic economist by contacting friends who may know of suitable openings, or by responding to advertisements in Job Openings for Economists. Assume that he can receive at most one offer from each source. With probability p_n he receives an offer through the network, and with probability p_f he receives it through the formal source. For each source, the wage offer is drawn from a common distribution $F(w)$. Thus, we assume that the distribution of wage offers is independent of the source (relaxed later). The immigrant worker accepts an offer if he receives at least one offer greater than his reservation wage. If he receives two offers, he chooses the higher offer, provided that it is higher than his reservation wage. Given the static nature of the model, there is no loss in generality in treating wage offers below the reservation wage as non-offers, and defining $F(w)$ over the range of wages greater than the reservation wage, and p_n and p_f as the probabilities of receiving an offer greater than this cutoff.

2.1 Network Strength

Network strength is defined by p_n; the higher the value of p_n, the stronger is the network. With probability $(1 - p_n) * (1 - p_f)$, the worker receives no offers, with probability $(1 - p_n) * p_f$, he receives only a formal offer, with probability $p_n * (1 - p_f)$, he receives only a network offer, and with probability $p_n * p_f$, he receives both types of offers. Therefore, the expected wage conditional on receiving at least one offer is,

$$E(w) = \frac{(p_f + p_n - 2p_f p_n)E(w|N = 1) + p_f p_n E(w|N = 2)}{(p_f + p_n - p_f p_n)} \tag{1}$$

where N is the number of offers received. It is straightforward to show that $E(w)$ is increasing in p_n (and p_f), provided the wage offer distribution is nondegenerate.

What about wages conditional on the method through which the job was found? The expected wage conditional on accepting a job through the network is,

$$E(w|n) = (1 - p_f)E(w|N = 1) + p_f E(w|N = 2) \tag{2}$$

which is independent of p_n. Similarly, the expected wage conditional on accepting a job through the formal source is,

$$E(w|f) = (1 - p_n)E(w|N = 1) + p_n E(w|N = 2) \tag{3}$$

which is increasing in p_n. It follows immediately that the gap between the expected wage conditional on finding a job through the network and the expected wage conditional on finding a job through the formal mechanism is decreasing in network strength, as defined by p_n. In other words, *the network premium is decreasing in network strength.*

Finally, consider the level of the difference in earnings conditional on job finding method:

$$E(w|n) - E(w|f) = (p_f - p_n)(E(w|N = 2) - E(w|N = 1)). \tag{4}$$

The sign of this difference depends on the relative probability of finding a job through the formal source and the network. If the network is less likely to produce a job than the formal source ($p_n < p_f$), then workers who find jobs through the network will have higher wages, on average, than those who find them through the formal source. On the other hand, if the network is more likely to produce a job than the formal source, then those finding jobs through networks will have lower wages than do those finding them through formal methods. This is the key insight in Montgomery (1992). The intuition for this counterintuitive result is straightforward. Consider an extreme example. Suppose the network almost never generates an offer (p_n is close to 0) while formal search almost always yields one (p_f is close to 1). In this scenario, almost all recent immigrants receive an offer from the formal source while very few receive an offer from the network. Therefore, those who accepted network jobs almost definitely chose between *two* offers, while those who accepted formal jobs almost all chose the *one* offer they had. Therefore, those in network jobs have higher wages compared to those in formal jobs even though the network is weaker than the formal source.

It should be noted that the result in equation (4) is sensitive to the assumption that the distribution of wages is the same for the two job sources. When the network distribution stochastically dominates, or is a mean preserving spread of the formal distribution, it is more likely that the expected wage conditional on finding the job through the network is higher than expected wage conditional on finding the job through the formal source irrespective of the relation between p_n and p_f.[3] Therefore, we now drop the assumption that the two sources draw from the same wage-offer distribution.

2.2 Differing Wage Distributions

There are a number of reasons that the distribution of offers may differ between the network and formal sources. Montgomery (1991) argues that workers referred to the employer through the network are better, on average, than those who apply directly. Dustmann, Glitz, and Schonberg (2010) 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 workers/job matches tend to be poorer for jobs found through the network. Therefore, we let the distribution of wages received through the network conditional on receiving an offer from the network be $F_n(w)$, and similarly, the distribution of the formal wages conditional on receiving an offer from formal channels be $F_f(w)$.

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

$$E(w) = \frac{p_f(1-p_n)E(w_f) + p_n(1-p_f)E(w_n) + p_f p_n E(w|N=2)}{(p_f + p_n - p_f p_n)}. \tag{5}$$

In contrast with the previous model, improvements in the strength of either the formal or network domains could lower expected wages conditional on getting a job. For example, if most network jobs offer very low wages relative to formal jobs, increasing the arrival rate of network jobs could lower the average wage among those getting jobs. A sufficient condition to rule out this possibility is that the mean of the network wage offer distribution is at least as large as the mean of the formal sector offer distribution. Of course, if we account for unemployment, a higher arrival rate of either type of offer must make workers better off.

The expected wage conditional on accepting a job through the network is,

$$E(w|n) = \frac{(1-p_f)E(w_n) + p_f E(w_n|w_n > w_f)\Pr(w_n > w_f)}{1 - p_f + p_f \Pr(w_n > w_f)} \tag{6}$$

which, as in the simpler model, is independent of p_n. Similarly, the expected wage conditional on accepting a job through formal channels is,

[3] In a slightly different context, Montgomery (1992) provides examples to show that even when both sources are equally strong and the network distribution stochastically dominates or is a mean preserving spread of the formal distribution, the expected wage conditional on network job could be lower than the expected wage conditional on formal job. Thus, the sign of the difference in expected wage conditional on job finding method can go in either direction when the network and formal distributions are different.

$$E(w|f) = \frac{(1-p_n)E(w_f) + p_n E(w_f|w_f > w_n)\Pr(w_f > w_n)}{1 - p_n + p_n \Pr(w_f > w_n)} \tag{7}$$

which, as before, is increasing in p_n. Therefore, even when we have differing offer distributions, it follows that the network premium is decreasing in network strength, as defined by p_n.

2.3 Effects at Percentiles of Observed Wage Distribution

It is important to note that while economists often focus on differences in means, our argument applies equally to percentiles of the observed wage distributions. The cdf of the observed network wage distribution is independent of p_n because conditional on receiving a network offer, the probability that the offer will be better than the formal offer is independent of p_n. In contrast, as described in the following proposition, the cdf of the observed formal sector wage distribution, $F_f(w|f)$, is decreasing in p_n.

Proposition 1 *Let $F_f(w|f)$ 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.

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

$$\frac{d}{dp_n}\left(\frac{F_f - \int_a^w p_n(1-F_n) f_f dx}{1 - \int_a^b p_n(1-F_n) f_f dx}\right) = \frac{\int_a^w F_n f_f dx - F_f \int_a^b F_n f_f dx}{\left(1 - \int_a^b p_n(1-F_n) f_f dx\right)^2} \tag{8}$$

Inspection of the numerator proves the second part of the proposition.
Now,

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

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

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

where

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

for $a < w < b$, from which it follows that

$$\frac{\int_{-\infty}^{w} F_n f_f dx}{\int_{-\infty}^{\infty} F_n f_f dx} < F_f.$$

and that

$$\frac{\int_{-\infty}^{w} F_n f_f dx - F_f \int_{-\infty}^{\infty} F_n f_f dx}{\left(1 - \int_{-\infty}^{\infty} p_n (1 - F_n) f_f dx\right)^2} < 0.$$

■

The proposition establishes that the percentile associated with any wage, except the highest and the lowest, in the observed formal sector wage distribution (wage conditional on formal sector employment) is reduced when the probability of a network offer increases. The intuition is straightforward. Any network offer beats a formal offer if it is greater than the formal offer and has no effect on the acceptance of formal offers above it. Most network offers will beat a very low formal offer but will not beat a very high formal offer. 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 workers accepts a high formal offer. The distribution of accepted formal offers shifts to the right. From this intuition, it should be clear that the effect on the percentiles does not depend on the continuity of the distributions although the math will be slightly messier if the distribution has mass points. Since the percentile of the observed formal sector distribution associated with each wage goes down as the probability of receiving a network offer increases, the wage associated with each percentile goes up. Moreover, since the observed network sector wage distribution is independent of the probability of receiving a network offer, we have the following:

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

The effect of network strength on the difference in the observed network and formal wages at each percentile suggests a potentially more powerful test of the model. Since there is no effect at the highest and lowest percentiles, there must be some percentile at which the effect is larger than the mean effect, and this difference might be sufficient to outweigh the reduced efficiency of estimating a percentile rather than the mean. Based on some earlier simulations, we anticipated that the effect of network strength on the network-formal wage differential will be largest (in absolute value) somewhere below the median. This is not a theorem, and it is certainly possible to generate counter-examples. To confirm our focus on the 25th percentile, we used the estimated offer probabilities and offer distributions from the structural model that best fit the data and found that these estimates also imply that the biggest wage change occurs at roughly the 25th percentile.

2.4 Summary of Predictions

In sum, in the simple case of one offer from each source, the model has the following predictions:

1. If the distribution of wage offers from the formal and network sources are identical, the expected wage is increasing in network strength, p_n.

2. If the distribution of wage offers from the formal and network sources are identical, the expected wage conditional on finding a job through the network is higher than the expected wage conditional on finding a job through formal methods if and only if the network is weaker than the formal source, i.e. $p_n < p_f$.

3. The distribution of wages in jobs found through the network is independent of network strength.

4. The distribution of wages in jobs found through formal means is increasing in network strength.

5. The difference between the expected wage conditional on finding a job through the network and the expected wage conditional on finding a job through formal methods is decreasing in network strength. In other words the network premium is decreasing in network strength.

6. At any given centile, the difference between the wage conditional on finding a job through the network and the corresponding centile wage conditional on finding a job through formal methods is decreasing in network strength. The magnitude of this effect varies across centiles.

In this case of one offer from each source, implications (3) - (6) hold even when the network offer distribution is not the same as the distribution of formal job offers.

2.5 Threats to the Theory

There are three primary concerns about the theory that must be addressed. The first is that the wage offer distributions may depend differentially on network strength. One possibility is that the formal wage offer distribution is unaffected by network strength, but the network wage offer distribution is improving in network strength. For example, if workers can receive more than one offer from the network, then the network offer distribution is really the first-order statistic of such offers. The best-network-offer distribution would be increasing in the probability of getting two (or more) offers, and therefore we might fail to confirm our prediction that the network premium falls as network strength rises. We will be looking at first jobs taken within six months of arriving in Canada. We do not expect that many members of our sample will have multiple offers through their network. Nevertheless, if we are wrong, we may fail to confirm the theory even if network strength acts as we suggest in our model. We note that in this case too, the distribution of accepted formal offers is increasing in network strength. If we find that the wages in jobs found through both mechanisms rise in the presence of close ties, this may indicate that our assumption that the network offer distribution is independent of network strength is wrong. We are less concerned about incorrectly rejecting the model than about incorrectly accepting it. This could happen if strong networks do not change the formal wage offer distribution, but worsen the network distribution. For example, if everyone expects that the new immigrant must work for his cousin, then his cousin may offer him a low wage. In this case, our prediction that the network-formal wage differential 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 3 above that the accepted network distribution is independent of network strength.

Second, if immigrants expect that they are likely to get an offer through their network, they may put less effort into finding a job through formal mechanisms when they have strong networks. This would lower the probability of a formal offer and therefore lower the distribution of wages among those who accept network jobs. This, too, would tend to help us confirm our principal hypothesis that the network premium is decreasing in network strength, but would once again lead to a violation of the prediction 3 above.[4]

Finally, the theory section assumes that workers are homogeneous. When workers are heterogeneous with respect to skill, the arrival rate of offers through either the network or formal channels may differ by skill level. Increasing the arrival rate of network offers will lower the network-formal wage differential for each individual through the mechanism described by our theoretical model. However, it may also change the relative skill levels of workers accepting jobs through the two channels. It is not obvious in what direction the mean skill differential between the two channels will change. If, when the probability of a network offer increases, the mean skill level of workers finding jobs through networks rises relative to those finding them through formal channels, the network-formal wage differential will be less negative than it would be in the absence of the endogenous compositional change. In this case, there is a risk that we will fail to confirm our main prediction that the network premium is decreasing in network strength, even though the mechanism through which network strength affects the labor market is the one proposed in the theory section: namely, that of increasing the probability of receiving an offer through the network. Conversely, if increasing the probability of a network offer lowers the mean skill level of workers finding jobs through networks relative to those finding them through formal channels, the network-formal wage differential will be more negative than it would be in the absence of the endogenous compositional change. This will make it easier to confirm the theory.[5]

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[4]Table 4 below shows that while a strong network increases wages in jobs found through formal means, it has no significant effect on wages in jobs found through the network. We also conduct a semi-parametric test of whether the network wage distribution with (without) close ties stochastically dominates the distribution without (with) close ties and find no evidence of this. This is discussed in detail in a later section.

[5]Two extreme examples may help. Suppose that regardless of network strength, high-skill workers always get both network and formal offers and therefore the number of high-skill workers in network jobs is independent of network strength. In contrast low-skill workers never get jobs through formal channels, but their probability of getting a job through the network goes up when the network is strong. In this case, relative to workers in jobs found through formal channels, jobs found through the network have a greater number of less skilled workers when the network is strong. This would make θ_4 negative, but not because of the mechanics of our model.

In contrast, suppose that all workers always get formal offers, but when the network is weak, 80 percent of high-skill workers but only 40 percent of low-skill workers receive offers through the network, and half of them choose the network offer. This implies that 40 percent of high-skill and 20 percent of low skill workers take jobs through the network while the remainder are in jobs found through formal channels. Now suppose that for both types the probability of a network offer rises by 25 percent to 100 percent and 50 percent, respectively, and for each group half of the offers are still accepted. The proportion of workers in network jobs who are low skill is independent of network strength (50 percent in each case), but their proportion among workers in formal jobs rises with network strength (from

3 Empirical Framework

We consider two potential measures of network strength. The first is the recent immigrant's network size (NS), as measured by the (log) proportion of working age population in his area of residence that consists of settled immigrants from his country of birth. Settled immigrants are those who have been in Canada for at least five years. Because we include dummy variables for each of the areas of residence, the specifications using proportions and absolute numbers are isomorphic. Our second measure of network strength is close ties **(**CT), the immigrant's response to whether he had at least one relative or friend in Canada when he first arrived.[6]

Our empirical strategy begins by examining whether the proposed measures of network strength do predict network use. In particular, a valid measure of network strength, as we interpret it, should be associated with a higher probability of having a network job and lower probabilities of both having a job found through formal mechanisms and being unemployed. In addition, if we treat the unemployed as having low wages, the measure should be associated with higher wages. If a measure has these properties, it may or may not affect other outcomes as predicted by our model, but, if it fails to have these properties, then it is clearly not a measure of network strength as we have defined it.

Validating Measures of Network Strength: To validate these proxies, we use multinomial logit to examine how they are related to an immigrant's job search outcome — unemployed U, in a job found through the network NJ, or in a job found through formal channels FJ. Thus, the log-odds ratio is given by,

$$\ln \frac{P^l_{ijk}}{P^U_{ijk}} = \delta^l_0 + \delta^l_1 NS_{jk} + \delta^l_2 CT_{ijk} + \delta^l_3 X_{ijk} + \omega^{1l}_j + \lambda^{1l}_k \tag{9}$$

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

We test the prediction on the wage distribution, using quantile regression at 75th percentile.[7] This approach is given by,

$$\ln w_{ijk} = \alpha_0 + \alpha_1 NS_{jk} + \alpha_2 CT_{ijk} + \alpha_3 X_{ijk} + \omega^2_j + \lambda^2_k + \upsilon_{ijk}. \tag{10}$$

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57 percent to 60 percent) so that the relative skill level of workers in formal jobs is lower when the network is strong. This could overturn our model's prediction of a negative θ_4.

[6]It is helpful that the recent immigrant is asked about the presence of close ties *just upon arrival*. This makes network strength exogenous to his subsequent labor market experience. This however does not preclude the possibility that immigrants with and without close ties may differ. For example, those without close ties might be more likely to immigrate to Canada only if they anticipate good labor market outcomes. We discuss identification extensively later in this section.

[7]Since thirty percent of new immigrants have not found employment within six months, it is not possible to estimate the effect of network strength on wages at lower centiles. We discuss estimates at the median in the text.

where w is the wage in the worker's first job after arriving in Canada, and we impute a very low wage to workers who have not yet found a job. The remaining variables are defined as in equation (9) above.

To preview the results, close ties has all the desirable properties expected of a good measure of network strength. However, we do not find that network size reduces formal employment or that it increases wages. We conclude that, however else network size operates, it is not by increasing what we have termed network strength, and therefore, the remainder of the empirical section focuses on the close ties measure.

Testing the Role of Close Ties: Our primary focus is to test whether the wage difference between those who found their jobs using networks and those who found them using formal mechanisms is related to the presence of close ties, the measure of network strength that survives our validation process. To do this, we augment equation (10) with an interaction between whether the individual found his first job through the network, NJ, and the presence of close ties, CT. This is given by the following difference in differences (DD) approach,

$$\ln w_{ijk} = \theta_0 + \theta_1 NS_{jk} + \theta_2 CT_{ijk} + \theta_3 NJ_{ijk} + \theta_4 (NJ_{ijk} * CT_{ijk}) + \theta_5 X_{ijk} + \omega_j^3 + \lambda_k^3 + \zeta_{ijk} \quad (11)$$

As explained earlier, if jobs found through networks and through formal channels draw on the same offer distribution, then if the immigrants' networks are stronger than formal channels (more likely to happen in the presence of a strong tie), the effect of finding a job through the network should be negative, while when they are weaker, it should be positive. Taking a job found through formal channels is more common in our sample than is taking a job found through the immigrant's network. This suggests that formal channels may be stronger than networks, at least when the network is weak. If so, we anticipate θ_3 will be positive. However, the assumption that the offer distribution is the same is very strong. Therefore, we view the sign of θ_3 as ambiguous.

The testable implications of our model are:

1. $\theta_2 > 0$: conditional on finding employment through formal means, wages are increasing in network strength,
2. $\theta_2 + \theta_4 = 0$: conditional on finding employment through the network, wages are independent of network strength, and
3. $\theta_4 < 0$: the difference between the expected wage conditional on finding a job through the network and the expected wage conditional on finding a job through formal mechanisms (the network premium) is decreasing in network strength

Testing the first two of these predictions relies on somewhat strong identifying assumptions. θ_2 might be positive for reasons unrelated to a higher probability of a network offer when the network is strong. If immigrants who have close ties are different from those who do not, then θ_2 could be spuriously positive (if those with close ties are more positively selected than those without close ties) or it could appear to be zero or negative (if those with close ties are more negatively selected than those without close ties). Essentially the same concerns apply to $\theta_2 + \theta_4$.

Consider the third prediction, $\theta_4 < 0$. It is important to understand what we are attempting to measure. It is the causal effect of increasing network strength on the *equilibrium wage differential* between workers who choose to accept a job through their network and those who choose to accept a job through formal channels. It is *not* the causal effect of network strength on the difference in the wages of workers randomly assigned to jobs obtained through each of the two channels. For a consistent estimate of θ_4, we require a condition similar to that in a standard differences-in-differences design. We require that if stronger networks do not increase the arrival rate of network offers, then the difference in the unmeasured characteristics of people with and without close ties would be independent of whether they happen to find their jobs through their network or through formal means:

$$\begin{aligned} E(\zeta_{ijk}|NJ_{ijk} &= 1, CT_{ijk}=1, Z_{ijk}) - E(\zeta_{ijk}|NJ_{ijk}=1, CT_{ijk}=0, Z_{ijk}) = \\ E(\zeta_{ijk}|NJ_{ijk} &= 0, CT_{ijk}=1, Z_{ijk}) - E(\zeta_{ijk}|NJ_{ijk}=0, CT_{ijk}=0, Z_{ijk}) \end{aligned} \tag{12}$$

where

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

In section 2.5 we discussed potential scenarios in which equation (12) may not be satisfied. While it is impossible to test a just-identifying assumption, we use two approaches to cast light on this issue. First, we examine the effect on the critical coefficient of controlling for measured skill. If this effect is small, then it is more plausible that the effect of shifts in the distribution of unmeasured characteristics, whether endogenous to the model or exogenous, is also small. Second, we test whether the network offer distribution is influenced by network strength. While we recognize that having close ties may be correlated with unmeasured immigrant characteristics, conditional on having a network job, if having a close tie has no effect on or raises wages, then it is less plausible that a stronger network differentially shifts low-skill workers to jobs found through the network.

As discussed in the theory section, the predictions regarding θ_2 and θ_4 apply not only to the conditional mean (OLS estimation), but also to all conditional quantiles except the highest and lowest. Also, we expect θ_4 to be most negative at quantiles below the median. We therefore also use quantile regression to estimate equation (11) at the 25th, 50th and 75th percentiles.

4 Data and Descriptive Analysis

4.1 Data

We use the 20 percent 2001 Census of Canada sample to calculate network size. The geographic unit used to characterize network size is the Census Metropolitan Area, CMA, or the Census Agglomeration, CA.[8] Henceforth, CMA/CAs will be collectively referred to as metropolitan areas.

[8]A census metropolitan area (CMA), or a census agglomeration (CA), is formed by one or more adjacent municipalities centered on a large urban area, known as the urban core. The census population count of the urban core is at least 10,000 to form a census agglomeration, and at least 100,000 to form a census metropolitan area. To be included in the CMA or CA, other adjacent municipalities must have a high degree of integration with the central urban area, as

Using the 2001 Census, we calculate the share of settled working-age (those between 22 and 64 years old) immigrant population in each metropolitan area from each source country. Measures of the wage distribution of the employed immigrant population from a particular country, residing in a particular metropolitan area, are also obtained from the Census.

Our remaining 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. We refer to this population as *recent immigrants*. The LSIC is a longitudinal survey with three waves: six months, two years and four years after arrival in Canada. We use only the first wave. Our target population in the LSIC sample is principal applicants[9] up to 64 years old and spouses and dependants between 22 and 64 years old who are in the labor force and living in metropolitan areas within Canada. Further, we exclude immigrants whose metropolitan area or country of origin is not known.[10] We also drop immigrants who were in prearranged jobs, or who were either self employed or in a family business.[11] Finally, we limit the analysis to immigrants who have at least one other member from their country in their metropolitan area,[12] and to those from metropolitan areas and source countries with at least ten immigrants in the LSIC sample.[13] The final LSIC sample consists of 6012 recent immigrants, from 60 different source countries and residing in 22 different metropolitan areas across Canada. There are a total of 511 source country-metropolitan area combinations in our data.

4.2 Descriptive Analysis

The largest sending countries and the largest receiving localities account for the vast majority of immigrants. According to the 2001 Census, the top ten source countries account for 51 percent of the working-age immigrant population. According to the LSIC, China followed by India are the top two source countries for recent immigrants, constituting 21 percent and 16 percent of the working-age recent immigrant population. Recent immigrants are settling in areas where there is an already large concentration of both native and immigrant population. The top five metropolitan areas together have 52 percent of Canada's working-age population, 75 percent of its working-age

measured by commuting flows derived from census place of work data. In the 2001 Census, there are 27 CMAs and 113 CAs across Canada.

[9]Principal applicant is the person upon whom the approval to immigrate was based.

[10]They consitute 0.5 percent and 1.2 percent of our target population, respectively.

[11]When asked about their first jobs, 7.5 percent of recent immigrants report being in prearranged jobs, 2.3 percent being self-employed and 0.5 percent in family businesses.

[12]This avoids issues around taking the log of 0 and identifying a mean wage when there are no observed settled immigrants. In practice, almost all of these observations are excluded on other criteria. We lose 0.9 percent of the remaining LSIC sample due to this restriction.

[13]Experimentation showed that trying to reduce this cutoff generated very large standard errors in our quantile regressions, presumably reflecting very small samples of employed immigrants in the metropolitan areas with few compatriots. We lose 5.7 percent of the remaining LSIC sample due to this restriction.

immigrant population and 83 percent of its recent working-age immigrants.

Table 1 shows the means for the variables in the first wave of the LSIC estimation sample. Almost three-quarters of the immigrants entered Canada on an economic visa. It is therefore not surprising that they are generally highly educated (almost 70 percent report having a Bachelor's or more education) and most speak either English or French very well. Despite their high skill level, average wages (roughly 400 Canadian dollars per week) of the employed are low.

By the time of the first wave, 30 percent reported that they found their first job through a relative or friend, which we define as a network job; 40 percent used other methods such as contacting the employer directly, responding to newspaper advertisements, employment agencies, the internet, referral from another employer or a union, to find their first jobs. We refer to these as formal jobs. The remaining 30 percent were unemployed.

The close ties measure is a binary variable. It takes the value 1 if the individual reports that he had at least one relative or friend in Canada when he first arrived. 89 percent of the recent immigrants have close ties. On average, an immigrant lives in a metropolitan area where 1.4 percent of the working-age population is from his country of birth and has been living in Canada for at least five years.

Two things must be noted at this point. First, finding the first job through the network ($NJ = 1$) does not necessarily imply the presence of a close tie (i.e. relative or friend in Canada on arrival, $CT = 1$). This is because immigrants may have found their network job through a friend made after migrating to Canada, a relative or friend not living in Canada, or through a compatriot or acquaintance who is neither a relative nor a friend. Thus, having a network job does not imply having a close tie or vice versa. Second, to the extent that job search is complex, the dichotomous measure of the "use of the social network" and the theoretical concept it wishes to capture are not perfectly related. For example, if a friend tells me that there are job openings where he works, and I apply and get a job there, do I report that I found the job through a friend, or that I applied directly to the employer? Thus, admittedly, the measure of use of network (i.e. $NJ = 1$) is imperfect. Thus, in contrast with much recent research (e.g. (Dustmann, Glitz, and Schonberg 2010); (Bayer, Ross, and Topa 2008); (Hellerstein, McInerney, and Neumark 2008)), we measure network use directly and therefore avoid the need to infer network use from the clustering of immigrants, but may miss some of the network use that their indirect measure can capture.

5 Results

5.1 Validating the Network Measures

Table 2 gives the marginal effects of network size and close ties on the probabilities of each of the three job-search outcomes from a multinomial logit (equation (9)). Having close ties is strongly related to the probability of accepting a network job within the first six months. At the means of the independent variables, close ties are associated with a 7 percentage point increase in the likelihood of accepting a network job, and a 5 percentage point decrease in the likelihood of accepting a formal job. It reduces the probability of unemployment by 2 percentage points, although this falls well short of statistical significance at conventional levels. The network size measure is also associated with an increase in the probability of accepting a network job, but the effect is very small; a 1 percent increase in the share of working age population in the recent immigrant's metropolitan area that is comprised of settled immigrants from his country of birth is associated with a .05 percentage point increase in the probability of accepting a network job. In contrast with close ties, network size is associated with a decrease in the probability of being unemployed, though the magnitude of this association is very small, and it has no effect on the probability of accepting a formal job. Thus, the relation between job search outcomes and close ties is broadly consistent with our expectations for a measure of network strength. While the results for network size are not entirely inconsistent with these expectations, they are also not strongly consistent.

Table 3 presents estimates of the relation between network measures and wages on first jobs found within six months. In addition to the network measures, and other control variables shown in the table, we also control for the first, second and third quartiles of wages of settled immigrants from the recent immigrant's country of birth living in his metropolitan area. This captures possible differences in the network offer distributions across immigrants from different metropolitan-country groups. The quartiles of the network distribution are not statistically significant (coefficients not shown in the table). We note in passing that while some of the coefficients on the controls have the anticipated sign, some do not. Immigrants with economic visas earn more than those with family visas who, in turn, earn more than those with refugee visas. Speaking English well is associated with higher wages, and women earn less than men. However, there is little evidence of a return to education or to experience.

Recall that if the wage offer distributions of jobs found through the network and through formal channels are similar, then the effect of network strength on observed wages should be positive. Column (1) presents the results of an otherwise standard OLS wage equation augmented with the network measures. The presence of close ties enters with a positive sign, and has a nontrivial point estimate (over 5 percent), and is significant at roughly the .06 level using a one-tailed test. We also see a small negative and statistically insignificant effect of network size on earnings. Therefore, either the network size measure does not have the predicted effect that a valid measure of network strength should have on wages, or the network wage offer distribution is significantly below the formal wage offer distribution.

To address the latter possibility, we turn to quantile estimation in column (2), in which we assign very low wages to the unemployed immigrants. Because there is no simple cluster correction for quantile estimates, a clustered bootstrap method is used to calculate the standard errors. This approach is problematic because, since clusters rather than observations are resampled, the number of observations can vary across replications, and will typically be smaller than the number in the actual sample. This should, therefore, produce upwards biased standard errors for the coefficients of variables for which cluster has little or no explanatory power. The standard errors on most of these variables rise somewhat but not greatly when we use the clustered bootstrap and some even fall. Therefore, the result of the cluster bootstrap is only reported for network size, since it is measured at the level of the cluster, and ordinary standard errors are reported for the remaining variables which are measured at the level of the individual. It is not possible to estimate the model for the 25th percentile because 30 percent of the recent immigrants are unemployed. In principle, it might be possible to estimate a median regression. However, experience revealed that the bootstrapped standard errors were sensitive to the value of the wage imputed to unemployed workers. Therefore, the second column of Table 3 presents the results of a 75th quantile estimate. The results of the 75th quantile estimates are consistent with those obtained using OLS on only employed workers. The relation between the wage and network size is small and statistically insignificant. In contrast, having a close tie is associated with roughly 6 percent higher wages at the 75th percentile and this effect is significant at the .05 level using a one-tailed test.

Based on the results for both job search outcomes and wages, we conclude that network size does not seem to capture the concept of network strength as we define it. We do not wish to imply that network size is unimportant. It is strongly related to the probability of accepting a job found through the network. However, the fact that it is neither associated with a reduction in the probability of having found a job through formal mechanisms nor with increased wages, tells us that either network size does not work in the way that network strength works in our model, or it is sufficiently correlated with unmeasured worker characteristics as to obscure this mechanism.

In contrast, the close ties measure passes our basic tests. It is associated with increased job-finding through networks and reduced employment found through formal means, and the point estimate suggests that it is also associated with a lower probability of unemployment. Moreover, close ties are associated with higher wages, both conditional on employment, and also when treating unemployment as having a low wage. This, of course, does not mean that network strength as measured by close ties works in the manner proposed in the theoretical model, but rather that it has passed minimal conditions consistent with its interpretation as a measure of network strength as we conceptualize it. Consequently, in the remainder of this paper, we focus on the close ties measure. We continue to include network size as an additional control, but it is not key to the analysis.

5.2 Augmented Wage Regression: Testing the role of Close Ties

Table 4 shows the results for the wage equation augmented with method of finding the first job (whether or not it was found using the network) and the interaction between this variable and our validated measure of network strength (presence of close ties) for first jobs found within six months.[14] As in the earlier table, for quantile regressions, only the standard error for network size is adjusted for clustering using a clustered bootstrap.

As discussed in the theory section, wages in formal jobs should be increasing in network strength. This prediction is confirmed using OLS. The point estimate of the effect is about 9 percent and is significant at the .05 level using a one-tailed test. There is a bigger and highly statistically significant effect at the 25th percentile. We also find strong evidence of an effect at the median and weak evidence of an effect at the 75th percentile.

The model also predicts that the wage distribution among those who find their job through the network should be unrelated to network strength. This effect is measured by the sum of the coefficients on close ties, and this variable interacted with network job. There is no consistent pattern to this estimate. It is positive in OLS and at the median and 75th percentile, but negative

[14] When interpreting the coefficients on close ties, network job and their interaction, it should be noted that the omitted group is that of recent immigrants in formal jobs and without close ties.

at the 25th percentile. In all cases, the sum is not statistically significant. As discussed in section 2.5, violation of this prediction would not be surprising, since immigrants with close ties might be better or worse workers, having different proclivities to receive network and formal offers, than immigrants without such ties. Nevertheless, as also discussed in section 2.5, most alternative explanations for a negative coefficient on the interaction between close ties and network job would imply that wages in network jobs would be lower for those with close ties than for those without them. The failure to reject the hypothesis of no effect on network wages therefore gives us more confidence that the identifying condition (12) is not violated for reasons extraneous to the model.

For reasons discussed earlier, our focus is on the interaction term. The theory section predicts that the coefficient on the interaction term will be negative at all quantiles, and there is reason to expect it to be more negative when we examine lower quantiles. As we should anticipate, column (2), pertaining to wages at the 25th percentile (of the conditional wage distribution), conforms closely with the predictions of the theoretical model. For wages at the 50th and 75th percentile, the interaction term is negative, as predicted, but is small and statistically insignificant. Overall, the network premium is decreasing in network strength as predicted by the theoretical model.

5.3 Testing threats to the Theory

5.3.1 Excluding Measured Skills

As discussed in section 2.5, the difference between the unmeasured characteristics of workers who find their job through their network and those who find it through formal channels could differ between those with and without close ties. While we cannot address this directly, we can examine the effect of excluding the measured characteristics from the comparison. In effect this asks whether an appropriately weighted sum of measured characteristics is correlated with the interaction term. While the absence of a correlation between the difference in measured characteristics and close ties would not guarantee that the difference in unmeasured characteristics is also uncorrelated with close ties, it would make the assumption more plausible. Moreover, as discussed earlier, if increasing the probability of a network offer is what changes the skill differential, then, finding such a change does not necessarily invalidate the empirical analysis.

Table 5 shows the effect of dropping the skills variables from the wage equation. We continue to control for country of birth, metropolitan area and the measures of wages among settled immigrants from the immigrant's country of birth in the metropolitan area where he lives. The most important point is that the results look quite similar to those with controls for skill-related variables. In particular, while controlling for skill makes the coefficient on the interaction term less negative for OLS, it makes it more negative at the 25th percentile, and both effects are relatively small.

Moreover, it is important to remember that we have an extensive set of controls for skill, in particular prior occupation in eight categories and measures of knowledge of the two national languages. 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 alter the results in an important way gives us a reasonable level of confidence in the results.

5.3.2 Network Wages and Close Ties

Second, we test whether network offer distribution is influenced by network strength. As already noted, for none of the estimates in Table 4, is the sum of the coefficients on close ties and close ties interacted with network job statistically significant. As a further test, we limit the sample to those with network jobs, and ask whether those with close ties have higher or lower mean wage conditional on observables. We find no evidence of a difference. The difference is close to zero and does not approach significance at conventional levels. We also conduct the Kolmogorov-Smirnov test of equality of the network wage residual distributions of those with and without close ties. Once again, we find no evidence of a difference in the distributions by network strength.

As discussed in section 2.5, most alternate explanations for a decrease in the network premium with network strength, require the network offer distribution to be inferior in the presence of close ties. We find no evidence of this, making it more plausible that the network premium decreases with network strength due to the mechanism captured by our theoretical model.

6 Structural Model

The results in the previous section are broadly consistent with the formal theoretical model presented earlier. However, it is not clear that the magnitudes of the effects can be reconciled with reasonable restrictions on the formal and network sector wage distributions. In this section, we ask whether a model with a single network wage offer distribution and a single formal wage offer distribution can fit the data as well as a model with two different network distributions that are characterized by network strength.

6.1 The Model

We assume that the immigrant receives offers with probability

p_f from the formal source
p_w from the network source if his network is weak
p_s from the network source if his network is strong.

Each log wage is drawn from a distribution given by

$$w_{ij} = X_i\beta + \alpha_j + \varepsilon_{ij}, \qquad \varepsilon_{ij} \tilde{} N(0, \sigma_j^2) \tag{13}$$

where i denotes the worker and j denotes the source (formal f, strong network s, weak network w) providing the offer. Thus α_j is a source-specific factor shifting the mean of the offer distribution. Note that we do *not* impose that the variance of the error is the same in all sectors, but we do assume that the errors are independent.

To derive the likelihood function, note that the probability that a worker with a strong network (close tie, CT) is unemployed is

$$(LF_u|CT = 1) = (1 - p_f)(1 - p_s) \tag{14}$$

and similarly for those with a weak network.

The likelihood of observing a worker with a strong network earning a given wage w, and employed in a job found through the network NJ, is

$$(LF(w, NJ)|CT = 1) = p_s \left((1 - p_f + p_f \Phi \left(\frac{\alpha_s - \alpha_f + \varepsilon_{is}}{\sigma_f} \right) \right) \phi(\varepsilon_{is}, \sigma_s^2). \tag{15}$$

The first term is the probability of getting a network offer. The last term is the density of the network offer when the network is strong. The term in parentheses is the probability that either the worker does not receive a formal offer or that this formal offer is less than the network offer, that is the probability that

$$X_i\beta + \alpha_f + \varepsilon_{if} < X_i\beta + \alpha_s + \varepsilon_{is} \tag{16}$$

or

$$P(\varepsilon_{if} < \alpha_s - \alpha_f + \varepsilon_{is}|\varepsilon_{is}). \tag{17}$$

The likelihoods for network offers when the network is weak and for formal offers when the network is strong and weak are derived similarly. Replacing ε with the residual, taking logs and summing across observations gives the likelihood function.

6.2 Results

The first column of Table 6 gives the results of estimating the complete model. We estimate that almost half the workers receive an offer through the formal source. When they have close ties (a strong network), workers receive an offer through their network almost as frequently suggesting that about one-fifth of such workers get two offers and that about 30 percent get no offers. In contrast, when their network is weak, new immigrants receive an offer through their network only about one-quarter of the time, implying that only about one-eighth of such workers get two offers and that nearly 40 percent get no offers.

The means of the three offer distributions are quite similar.[15] The residual variance of the offer distribution is somewhat, but not dramatically lower among network jobs than among jobs found through formal mechanisms. We can neither reject the hypothesis that the means of the weak and strong network offer distributions are the same ($t = 0.21$), nor the hypothesis that their standard deviations are the same ($t = 1.50$).

Therefore in the second column, we restrict the offer distribution in network jobs to be independent of network strength. As can be seen from comparing the log-likelihoods, we cannot reject this constraint ($\chi^2(2) = 1.38$). The means of the network and formal offer distributions continue to be similar and the standard deviations of the two distributions are only modestly different.

Finally in the last column, we ask whether we can reject the hypothesis that the network and formal offer distributions are the same. Despite the similarity of the distributions in the second column, this hypothesis is easily rejected at any conventional level of significance ($\chi^2(2) = 39.04$).

[15]Note that the levels 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.

Thus the results of the structural model are very much in line with the theoretical model: network strength is associated with a greater likelihood of receiving a job offer through the network but with, at most, a negligible effect on the offer distribution.

That said, we must acknowledge that the reduced-form and structural results are not perfectly consistent. The coefficients in the 25th centile estimates are larger than implied by our structural estimates. Simulating the distributions implied by the structural model establishes that while the effects at the 25th quantile should be larger than at the median or 75th quantile, each of the coefficients on close ties, network job and their interaction should be smaller in absolute value. This suggests that the log-normality assumption used in the structural model may be violated.

7 Summary and Conclusions

We developed a theoretical model of the importance of networks for recent immigrants seeking jobs and derived the equilibrium results for immigrants with strong and weak networks. In our model, network strength is defined by the probability of receiving a job offer from the immigrant's network. The model predicts that the network-formal wage differential is decreasing in network strength and that this effect should be most pronounced at lower quantiles. We tested these implications on a nationally representative sample of recent immigrants into Canada. The empirical strategy to carry out comparative statics first required examining network size and close ties as potential measures of network strength. It is apparent that network size does not operate in the manner that our theory ascribes to network strength. However, when close ties is used as a measure of network strength, the model's predictions are not rejected in any of the specifications, and are strongly supported for wages at the lower end of an individual's acceptable wage distribution. This suggests that, the presence of at least one relative or friend in the host country at the time of the immigrant's arrival, increases the probability that he receives an offer through his network.

We also tested the model by estimating a simple structural model in which network and formal offers are drawn from two log-normal distributions. The estimates were consistent with the presence of close ties resulting in a large increase in the probability of a network offer, and no effect on the network offer distribution. Our results suggest that a model in which the primary role of strong social ties is to increase the arrival rate of offers from the network distribution is consistent with the data. Our results also suggest that the offer distributions in the formal and network sectors differ only modestly, so that Montgomery's (1992) model can be applied.

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 help in the economic assimilation of recent immigrants. Our findings suggest that immigrants with close social ties enjoy a faster arrival rate of jobs. We do not address other issues related to immigrant dispersion, including the longer term labor market effects of immigrant enclaves.

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Table 1: Summary Statistics (First Wave LSIC Estimation Sample)

Variable	Mean	Std. Dev.	Observations
Dependent Variables			
Network Job	0.30		6012
Formal Job	0.40		6012
Unemployed	0.30		6012
Weekly Wage (CAD)	406	276	4007
Key Explanatory Variables			
Network Size (not in logs)	0.014	0.014	6012
Close Ties	0.89	0.31	6012
Additional Explanatory Variables			
Female	0.43	0.49	6012
Age	34.6	8.4	6012
Married	0.81	0.39	6012
Number of children	0.89	1.04	6012
Speaks English Well	0.65	0.48	6012
Speaks French Well	0.12	0.32	6012
Lived in Canada Before	0.05	0.23	6012
Principal Applicant	0.72	0.45	6012
Education			
Less than High School	0.06		5976
High School	0.08		5976
Some College	0.05		5976
College	0.12		5976
Bachelor	0.46		5976
Master and above	0.23		5976
Visa Category			
Economic Visa	0.74		5951
Family Visa	0.22		5951
Refugee Visa	0.03		5951
Occupation before migrating			
Manager	0.02		5966
Professional	0.38		5966
Paraprofessional	0.14		5966
Clerical	0.03		5966
Laborer	0.002		5966
New Worker	0.25		5966
Student	0.04		5966
None	0.15		5966

Table 2: Influence of Network Measures in Finding First Jobs within six months

	Formal Job	Network Job	Unemployment
Predicted Probability of Positive Outcome (at means of independent variables)	0.44	0.26	0.30
	Multinomial Logit Marginal Effects (at means of the independent variables)		
Network Size	0.003	0.049***	-0.052***
	[0.015]	[0.015]	[0.013]
Close Ties	-0.054***	0.074***	-0.020
	[0.017]	[0.022]	[0.025]
Log Pseudo-likelihood[1]		-5687.3	
Observations		5869	
Clusters		499	

Robust standard errors in brackets, clustered at the metropolitan-country level. Full specification includes the 'Additional Explanatory Variables' described in Table 1; also includes metropolitan and country of birth dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.10$;
1 'Pseudo-likelihood' because with clustered data we do not have independent observations.

Table 3: (Log) Wages for First Jobs within six months

	OLS	Quantile Regressions[1]
		0.75
	(1)	(2)
Network Size	-0.018	0.012
	[0.027]	[0.043]
Close Ties	0.059	0.058*
	[0.038]	[0.035]
Female	-0.219***	-0.197***
	[0.028]	[0.026]
Age	-0.002	-0.007***
	[0.002]	[0.002]
Married	-0.009	-0.046
	[0.038]	[0.034]
Kids	-0.028**	-0.015
	[0.012]	[0.014]
Speak English well	0.057*	0.052**
	[0.032]	[0.026]
Speak French well	-0.116	-0.135**
	[0.086]	[0.064]
Lived in Canada before	0.059	0.144**
	[0.075]	[0.056]
Principal Applicant	0.036	-0.014
	[0.044]	[0.039]
Less Than High School	0.079*	0.077
	[0.041]	[0.053]
High School	0.083**	0.062
	[0.034]	[0.048]
Some College	0.069*	0.058
	[0.041]	[0.057]
College	-0.049	-0.012
	[0.037]	[0.040]
Bachelor's Degree	-0.008	-0.036
	[0.024]	[0.028]
Family Visa	-0.104*	-0.041
	[0.060]	[0.046]
Refugee Visa	-0.194**	-0.042
	[0.079]	[0.080]
Observations	3,786	5,461

For OLS, standard errors clustered at metropolitan-country level, R squared is 0.158. *** $p<0.01$, ** $p<0.05$, * $p<0.10$; Omitted categories for education and visa are Master's and above and Economic visa, respectively. Additional controls include 25^{th}, 50^{th}, 75^{th} percentile wages of the immigrant's network, dummies for occupation before migrating to Canada, and metropolitan and country of birth dummies.

1. Quantile regression includes the unemployed, where very low wages were assigned to them

Table 4: (Log) Wages, Method of Job Finding and Network Strength

	OLS	Quantile Regressions		
		0.25	0.5	0.75
	(1)	(2)	(3)	(4)
Network Size	-0.016	-0.009	0.003	-0.036
	[0.027]	[0.058]	[0.037]	[0.037]
Close Ties	0.088*	0.156***	0.082**	0.059
	[0.053]	[0.042]	[0.039]	[0.046]
Network Job	0.038	0.245***	0.038	-0.042
	[0.079]	[0.070]	[0.066]	[0.076]
Network Job*Close Ties	-0.084	-0.243***	-0.062	-0.019
	[0.086]	[0.073]	[0.069]	[0.080]
Observations	3,786	3,786	3,786	3,786

For OLS, standard errors clustered at metropolitan-country level, R squared is 0.159
Full specification includes the 'Additional Explanatory Variables' described in Table 1, quartiles of the network distribution, metropolitan and country of birth dummies
*** $p<0.01$, ** $p<0.05$, * $p<0.10$;

Table 5: (Log) Wages, Method of Job Finding and Network Strength, Skill Bias Check

	OLS		0.25 Quantile Regressions	
	All Controls	Excluding all Skills	All Controls	Excluding all Skills
	(1)	(2)	(3)	(4)
Close Ties	0.088*	0.081	0.156***	0.166***
	[0.053]	[0.053]	[0.042]	[0.055]
Network Job	0.038	0.019	0.245***	0.182**
	[0.079]	[0.077]	[0.070]	[0.093]
Network Job*Close Ties	-0.084	-0.105	-0.243***	-0.205**
	[0.086]	[0.088]	[0.073]	[0.097]
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
Observations	3,786	3,786	3,786	3,786
R-squared	0.159	0.137		
Clusters	330	330		

For OLS, standard errors clustered at metropolitan-country level. Full specification in each column includes the 'Additional Explanatory Variables' described in Table 1, quartiles of the network distribution, metropolitan and country of birth dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.10$;

Table 6: (Log) Wages, Estimated Offer Distributions

	(1)	(2)	(3)
Prob. Formal Offer	0.48	0.48	0.48
	(0.01)	(0.01)	(0.01)
Prob. Network Offer (strong)	0.44	0.44	0.44
	(0.01)	(0.01)	(0.01)
Prob. Network Offer (weak)	0.25	0.25	0.25
	(0.02)	(0.02)	(0.02)
Mean formal offer	5.73	5.73	5.65
	(0.13)	(0.13)	(0.13)
Std. Dev. formal offer	0.65	0.65	0.61
	(0.01)	(0.01)	(0.01)
Mean network offer (strong)	5.72	5.72	[2]
	(0.13)	(0.13)	
Std. Dev. network offer (strong)	0.56	0.57	[2]
	(0.01)	(0.01)	
Mean network offer (weak)	5.67	[1]	[2]
	(0.14)		
Std. Dev. network offer (weak)	0.60	[1]	[2]
	(0.04)		
Log-likelihood	-9389.20	-9389.89	-9409.41

Standard errors in parentheses. Additional controls: network size, mean wage settled immigrants from country of birth and 'Additional Explanatory Variables' described in Table 1

[1] Weak and strong network offer distributions constrained to be equal

[2] All offer distributions constrained to be equal