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The Role of Social Ties in the Job Search of Recent Immigrants

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The Role of Social Ties in the Job Search of Recent Immigrants[1*]

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Abstract
We show that among workers whose network is weaker than formal (non-network) channels, those finding a job through the network should have higher wages than those finding a job through formal channels. Moreover, this wage differential is decreasing in network strength. We test these implications using a survey of recent immigrants into Canada. At least at the lower end of an individual's wage distribution above his reservation wage, finding a network job is associated with higher wages for those with weak networks, and the interaction between network strength and finding a job through the network is negative as predicted.

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Executive Summary

This paper examines the role played by social networks in the job search process of recent immigrants. Participants in the labour market do not have complete information. In particular, job seekers do not know about all existing job vacancies that may potentially be good matches. In this context, social networks may provide a valuable informational resource. In fact, one would expect the problem of information scarcity to be more severe for new immigrants. For example, new immigrants may face language barriers that hinder access to information from formal/non-network sources. It is then natural for them to rely on people they know for information about potential jobs.

In examining the role played by social networks in influencing the labour market outcomes of immigrants, the existing literature has mainly looked at the effects of living in ethnic enclaves. The underlying belief is that social networks among immigrants are likely to be larger within ethnic enclaves. Except for unusual circumstances such as refugee programs that randomly assign immigrants to their locality, it is typically difficult to assess the effect of living in an enclave on immigrant outcomes. If booming communities attract many immigrants, it will appear that immigrants do better if they move where there are lots of immigrants. On the other hand, if, for example, immigrants with poor knowledge of the host country language tend to move to immigrant enclaves, it may appear that enclaves hurt immigrants.

In contrast with this literature, although we also examine the role of *network/enclave size*, we focus on the effect of *network strength*. In our theoretical section, strong networks are those with a high probability of producing a job offer. In our empirical work, we show that an immigrant who settles near a relative or friend on arrival in Canada is more likely to find a job through a network. We define a strong social tie as the presence, upon arrival, of at least one relative or friend in the locality where the recent immigrant initially settled and use this variable to capture network strength.

We develop a theoretical model that shows that among workers whose network is *stronger* than formal (non-network) channels (i.e. the offer arrival rate from networks is greater than from formal channels), those who find a job through the network should have *lower* wages than those who find a job through formal channels, and this wage differential is predicted to be increasing in absolute value in network strength. The empirical strategy focuses on this interaction between network strength and job-finding method. This approach greatly mitigates the problem of omitted variables bias which, as discussed above, typically plagues studies that try to examine network-size effects.

We combine census data with the Longitudinal Survey of Immigrants into Canada, a nationally representative sample of recent immigrants arriving in Canada between October 1, 2000 and September 30, 2001. We use these data to examine the role played by strong social ties in the job search of these new immigrants entering the Canadian labour market.

The presence of a strong social tie is significantly associated with finding a job through the network (but only insignificantly with finding a job) suggesting that this variable is a good proxy for network strength. We also find that larger networks/enclaves are associated with a higher probability of finding both network and formal jobs although these effects dissipate within a few years after the immigrants' arrival, and we have already noted the need for caution in interpreting this correlation.

Strong networks are also associated with higher wages at the lower end of an immigrant's wage distribution but have only a modest relation to their overall wage. If we compare two otherwise similar groups of recent immigrants, the group with strong ties earns a statistically insignificant 5.6% more, on average. However, the 25th percentile of the strong network group's wage distribution is 9.4% higher and the median is 4.7% higher. Again, it is not clear whether this relation is causal although the result is consistent with the expectation that immigrants with stronger ties will have higher wages.

The main innovation in the research is our examination of wages conditional on whether the immigrant found a job through a network or more formal means and to use the results to assess the importance of strong social ties. In the absence of strong social ties, those finding their first jobs through networks have weekly wages that are similar to those finding them through formal means. With strong networks, as predicted, those finding their jobs through the network have *lower* wages compared to those finding them through formal means, but the difference is small and again statistically insignificant. In contrast, there is an important effect at the lower end of an individual's potential wage distribution. If we compare two otherwise similar groups of recent immigrants, both of whom do not have strong network ties, the 25^{th} percentile of the group finding its job through the network earns 17.2 percent more than the same percentile of those doing so using formal means. More importantly, if we do the same comparison (of 25^{th} percentile wages) for those with strong ties, those who are in network jobs earn a wage that is only 0.8 percent higher compared to those who obtained jobs through formal channels. Thus, at this level, the network premium (network-formal wage differential) is 16.4 percent lower for those with strong social ties compared to the network premium for immigrants without these ties.

Therefore the network premium is decreasing in network strength as predicted by the theoretical model, suggesting that at this end of the wage distribution the presence of a strong social tie increases the offer arrival rate of jobs from the network. We interpret this as suggesting that, everything else equal, new immigrants with strong ties are more likely than are immigrants without such ties, to receive an offer through their network. However, relative to weak ties, strong ties do not increase or decrease the arrival rate of network jobs at the upper end of the immigrant's potential wage distribution, only at the lower end of this distribution.

It is often argued that immigrants tend to cluster together because the presence of established immigrants facilitates assimilation of new arrivals, both in the labour 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 strong social ties in their localities enjoy a faster arrival rate of jobs, at least at the lower end of their wage distribution. Our paper does not address other issues related to immigrant dispersion, including the longer-term labour market effects of immigrant enclaves.

1 Introduction

Participants in the labor market do not have complete information. In particular, job seekers do not have information about all existing job vacancies that may potentially be good matches. In this context, social networks may provide a valuable source of information. In fact one would expect the problem of information scarcity to be more severe for new immigrants. For example, new immigrants may face language barriers that hinder their access to information through formal/non-network sources. It is then natural for them to rely on people they know for information about potential jobs. In this paper we examine the role played by social networks in the job search of recent immigrants. We develop a theoretical model that brings out the importance of strong social ties in the host country and then test the implications of the model using a nationally representative survey of recent immigrants to Canada.

In examining the effects of social networks on labor market outcomes of recent immigrants, the existing literature has mainly looked at the effects of living in ethnic enclaves, suggesting an underlying belief that social networks among immigrants may be stronger in ethnic enclaves. There is less agreement about how enclaves affect immigrants in the labor market. An important channel by which enclaves influence economic assimilation is by providing their members with a self-contained labor market. There are many reasons why employers within an enclave may prefer to hire individuals from their own country (Borjas 2000). By employing their compatriots, frictions at work arising from differences in language and work habits are reduced. Further, employees may also have a better understanding of consumers' tastes within the enclave, which may help the firm to better serve its market. On the other hand, by providing jobs targeted towards its members and steering them into certain occupations, enclaves may limit their search horizons. They could therefore preclude jobs in the broader labor market, that may have been better matches. Living in an enclave may also be associated with a lower rate of acquisition of host country skills, e.g. language, which may reduce the chances of moving to better jobs ((Lazear 1999) and (Berman, Lang, and Siniver 2003)). Furthermore, according to the *human capital externalities* model, the efficiency of segregation depends on the quality of the enclave, i.e. the stock of human capital ((Edin, Fredriksson, and Aslund 2003), (Borjas 1992) and (Borjas 1995)). For example, if skilled members of an ethnic group live together, then newcomers may benefit from interacting with other settled members of their group while the opposite may be true if unskilled members congregate in the same geographic area. Thus, the effect of living in an enclave on immigrants' labor market experience is ambiguous and needs to be examined empirically.

The main problem encountered in trying to estimate the causal effect of networks is one of omitted variables bias. First, there may be unobserved factors that make members of a particular country more suitable for certain jobs and/or there may be location specific factors that result in good labor market outcomes. For example, new immigrants to areas where existing immigrants have a low unemployment rate may also have a low unemployment rate, not because the existing immigrants are better able to help the new arrivals, but because labor market conditions are generally favorable there. Second, there may be important unmeasured differences between individuals who choose to locate near other members of their ethnic group and those who do not.

Some papers have addressed omitted variables bias by using instrument variable techniques for network characteristics. Munshi (2003) studies Mexican migrants in the United States. He proxies the individual's network by the proportion of the sampled individuals from his community who are located in the U.S. in that year. To avoid endogeneity problems, he uses lagged rainfall in the origin-community as an instrument for the size of network at the destination. He finds that the same individual is more likely to be employed and to hold a higher paying non-agricultural job when his network is exogenously larger. Edin, Fredriksson, and Aslund (2003) study the effects of ethnic enclaves on earnings using data from an immigrant policy initiative in Sweden, when government authorities distributed refugee immigrants across locales based on the availability of housing. They argue that this provides a natural experiment which allows them to estimate the causal effect of living in enclaves. They instrument current location attributes with attributes of the initial assigned location and find that enclaves improve labor market outcomes for less skilled immigrants. Although these papers have effectively addressed the endogeneity of network characteristics, their results are specific to their contexts, namely Mexican immigrants to the United States and refugees in Sweden, both quite atypical immigrants, and may not extend to other scenarios.

In this paper we examine the importance of networks using a nationally representative sample of recent immigrants to Canada. The social network of a recent immigrant can be characterized in many ways. Here we use two variables to capture the network structure. The first is *network strength,* indicated by the presence of at least one relative or friend in the recent immigrant's area of residence in Canada, just at the time of arrival.[1] The second is *network size,* measured by the share of the local area population from his country of birth. The use of the network strength variable is a novel approach and captures network influence arising from the presence of at least one strong social tie close by. Network size captures the influence of weak/potential social ties or the enclave effect. We study the effect of these dimensions of network structure on the recent immigrant's labor market outcomes.[2] This is done in two steps. First we adopt a difference in differences approach to estimate the network effect. This approach addresses some of the bias arising from unobservable group/location characteristics, but may still suffer from bias arising mainly due to individual specific unobservables. We undertake this exercise mainly because it directly estimates the network effect and permits comparison of our results with the existing literature.

In the next step we empirically test the implications of the theoretical model developed here. The model shows that among workers whose network is *stronger* than formal channels are (in other words whose network provides a greater probability of an offer than do formal channels), those who find a job through the network should have *lower* wages than those who find a job through formal channels, and this wage differential is decreasing in absolute

[1] For our empirical estimates it is important that the recent immigrant is asked about the presence of a strong social tie in his neighborhood, *just upon arrival.* This makes network strength exogenous to his subsequent labor market experience.

[2] Discussion about the nature of network ties that help find jobs has its origins in sociology. Granovetter (1973) defines the strength of a tie as a combination of the amount of time, the emotional intensity, the intimacy and the reciprocal services which characterize the tie. This is a very intuitive definition and captures the closeness of an interpersonal relationship. Bridges and Villemez (1986) and Marsden and Hurlbert (1988) find evidence that, after controlling for worker characteristics, there is no significant relation between strength of tie used to find the job and the wage in the job. These papers have focused on the relation between the type of tie *actually used* to locate a job and the job's characteristics. The 'networks as resources' argument made by Campbell, Marsden, and Hurlbert (1986) suggests that the entire *network structure* may be the crucial independent variable and must be taken into account when attempting to examine the effect of social networks on labor market outcomes.

value in network strength. Our empirical strategy tests the latter implication by using the interaction between network strength and job finding method. We overcome the omitted variables problem by focussing on this interaction term.

We find that a stronger network helps a recent immigrant find his first job through his social network. A larger network is associated with a higher probability of finding a job and also a higher probability of finding the first job using the social network, but the effects of network size are small in magnitude. The difference in differences approach provides some evidence of a positive relation between wages and network strength and little evidence of a network size effect. When the difference in differences model is augmented with an interaction between job finding method and network strength, we find that the implications of the theoretical model are confirmed for jobs at the lower end of an individual's acceptable wage distribution (i.e. wage distribution above his reservation wage). At this end of his wage distribution, finding a network job is associated with higher wages for those with weak networks. Also, the interaction between network strength and finding a job through the network is negative, suggesting that at the lower end of his acceptable wage distribution, the presence of at least one strong social tie in his neighborhood upon arrival increases the number of job offers he receives from his network.

In section 2 we develop a 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 gives the conclusions.

2 THEORETICAL MODEL

The model draws heavily on Montgomery (1992). The key result regarding the expected wage conditional on job-finding method can be found there in general form by translating variables appropriately.

Consider a recent immigrant looking for jobs. He faces two sources of job offers, the network source, and the formal/non-network source. Suppose that with probability p_n he receives an offer through the network, and with probability p_f he receives a job offer through the formal source. Also assume that he can receive at most one offer from each source. In each case, the wage offer for the job is drawn from a common distribution, with distribution function $F(w)$. Thus, the assumption here is that the distribution of wage offers is independent of the source. Also assume that immigrants are homogenous in their skill level.

The model is set in discrete time and there is a single time period. 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. For the moment, 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

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.

The expected wage conditional on receiving at least one job 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 job offers received. It is straightforward to show that $E(w)$ is increasing in p_n (and p_f), provided that the expected wage is increasing in the number of offers, which it will be if the distribution of offers 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.

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 also 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.

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 method 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 networks will have higher wages, on average, than those who find them through formal methods.* Note that, if the network is more likely to produce a job than the formal source, then those finding jobs through networks will have lower wages vis-à-vis those finding them through formal methods. This is the key insight in Montgomery (1992).

The intuition for this counterintuitive result is relatively straightforward, especially in the case of one contact of each type. To explain the intuition consider an extreme example. Suppose, in a given time period, the network almost never generates a job offer (p_n is close to 0) while formal search almost always yields an offer (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 most likely 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.

The result on the sign of the difference in earnings conditional on job finding method 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 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]

[3] However, in a slightly different context, Montgomery (1992) provides examples to show that even when both sources

2.2 Differing Wage Distributions

Let the distribution of wages received through the network conditional on receiving an offer be $F_n(w)$, and similarly, the distribution of the formal wages conditional on receiving an offer be $F_f(w)$.

The expected wage conditional on receiving a job offer is,

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

As before, improvements in the strength of either the formal or network domains will raise expected wages.

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

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

which, as in the simpler model, is independent of p_n.

The expected wage conditional on accepting a job through formal means is,

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

which, as before, is increasing in p_n. Therefore, it continues to be true 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 formal mechanisms, is decreasing in network strength, as defined by p_n.

In sum, in the simple case of one offer from each source, the model has the following predictions regarding network strength, (the probability of finding the job through the network):

1. The expected wage is increasing in network strength.
2. If the distribution of wage offers in the formal and network sectors 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 $p_n < p_f$.
3. 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 this simple case, implications (1) and (3) hold even when the network distribution is not the same as the distribution of formal job offers.

are equally strong and the network distribution stochastically dominates or is a mean preserving spread of the formal distribution, expected wage conditional on network job could be lower than 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.

2.3 Multiple Contacts

The model of network strength developed above can be looked at as the reduced form of a more complicated model in which individuals have multiple formal and network contacts. In this case, p_n and p_f are the probabilities of getting at least one offer through network and formal contacts, respectively.

Consider the following simplified version of Montgomery's model. An individual has N network contacts to jobs and M formal contacts. As before, the probability that *each* contact produces an offer is given by, p_n and p_f, and conditional on an offer, wages are drawn independently from a distribution $F(w)$. Then, the probability that a contact of type i produces a wage of no more than w is,

$$\Phi_i(w) = 1 - p_i(1 - F(w)) \tag{8}$$

and the probability that all contacts produce a wage no higher than w is,

$$H(w) = \Phi_f^M(w)\Phi_n^N(w). \tag{9}$$

The densities of accepted network and formal wages are given by,

$$h_n(w) = Np_n f(w)H(w)/\Phi_n \tag{10}$$
$$h_f(w) = Mp_f f(w)H(w)/\Phi_f \tag{11}$$

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

$$\begin{aligned} E(w|n) &= \frac{\int_{w_r}^{\infty}(wNp_n f(w)H(w)/\Phi_n)\,dw}{\int_{w_r}^{\infty}(Np_n f(w)H(w)/\Phi_n)\,dw} && (12)\\ &= \frac{\int_{w_r}^{\infty}(wf(w)H(w)/\Phi_n)\,dw}{\int_{w_r}^{\infty}(f(w)H(w)/\Phi_n)\,dw} && (13)\\ &\equiv \frac{\int_{w_r}^{\infty}(wD(w))\,dw}{\int_{w_r}^{\infty}(D(w))\,dw} && (14)\end{aligned}$$

where w_r is the reservation wage, and $D(w) \equiv \frac{f(w)H(w)}{\Phi_n}$. Similarly, the expected wage conditional on getting a job through the formal source is,

$$\begin{aligned} E(w|f) &= \frac{\int_{w_r}^{\infty}(wMp_f f(w)H(w)/\Phi_f)\,dw}{\int_{w_r}^{\infty}(Mp_f f(w)H(w)/\Phi_f)\,dw} && (15)\\ &= \frac{\int_{w_r}^{\infty}\left(wD(w)\frac{\Phi_n}{\Phi_f}\right)dw}{\int_{w_r}^{\infty}\left(D(w)\frac{\Phi_n}{\Phi_f}\right)dw}. && (16)\end{aligned}$$

Define ϕ^* by

$$\int_{w_r}^{\infty}(D(w))\,dw = \int_{w_r}^{\infty}\left(D(w)\frac{\Phi_n}{\Phi_f}\phi^*\right)dw. \tag{17}$$

Such a ϕ^* exists, and is unique, if $\frac{\Phi_n}{\Phi_f}$ is monotonic in w.

Then $E(w|n) > E(w|f)$ if and only if

$$\int_{w_r}^{\infty} (wD(w))\, dw > \int_{w_r}^{\infty} \left(wD(w) \frac{\Phi_n}{\Phi_f} \phi^* \right) dw \tag{18}$$

Now recall that

$$\frac{\Phi_n}{\Phi_f} \phi^* = \frac{1 - p_n(1 - F(w))}{1 - p_f(1 - F(w))} \phi^* \equiv R(w), \tag{19}$$

which is everywhere positive, and is decreasing in w if and only if $p_n < p_f$. Suppose that this condition holds. By (17), $R(w) < 1$ for sufficiently high w and $R(w) > 1$ for sufficiently low w. In effect, $R(w)$ puts less weight to the density function for high values of w and more weight for low values, meaning that the conditional distribution of the network wages stochastically dominates that of the formal sector wages, and thus has a higher mean. The opposite condition holds if $p_n > p_f$. Thus, even in the case of multiple contacts, implication (2), listed in the end of sub-section 2.2, holds.

In the case of multiple contacts, a proof for the monotonicity result, namely, the difference between the conditional wages is monotonic in p_n, is not given. With multiple contacts, an increase in the probability of getting an offer through each member of the network will change, not only the overall probability of getting an offer, but also the distribution of the highest wage offer received through the network. Therefore, the proofs in sub sections 2.1 and 2.2 above, would not apply. However, the fact that when networks are stronger than formal sources, conditional wages are higher for formal jobs than network jobs, and that, when networks are weaker than formal sources, the opposite is true, reinforces the decision to focus empirical work on the interaction between network strength and job-finding channel.

2.4 Endogenous Reservation Wages and Unemployment

Allowing for multiple periods, and therefore, endogenous reservation wages and unemployment duration, would further complicate the model. Following the standard sequential search framework, it is imposed that the assumptions above apply in each period. In other words, the worker receives an offer through the network with probability p_n, and this offer is drawn from a distribution $F_n(w)$, and similarly for offers obtained through formal mechanisms. Once the worker receives and accepts an offer, there is no further search. The worker seeks to maximize the present value of his lifetime earnings (or more generally utility, if there is value to leisure). This framework ensures that the worker's search strategy relies on the reservation wage property. If a worker receives an offer above his reservation wage in any period, he will accept that offer, unless he receives two offers that period, in which case he accepts the higher offer.

It is well known that in such models, the reservation wage is increasing in the arrival frequency of offers, and that it increases as the offer distribution shifts to the right. Under special circumstances, the increase in the reservation wage engendered by an increase in the offer arrival rate can be sufficient to increase unemployment. Log concavity of the offer distribution is sufficient to eliminate this somewhat perverse result. However, here, there is a mixture of offer distributions, and there is no known intuitive condition which eliminates the possibility that an increase in network strength, or the effectiveness of formal mechanisms, increases unemployment. Nevertheless, as discussed in Montgomery, one would generally expect raising p_n and/or p_f to increase the employment rate.

The more serious problem is that raising the reservation wage can change the difference in the expected wage from one and two offers in equation (4), or the equivalent in equations (7) and (6). Therefore, the model cannot establish, as a theorem, that the wage difference between jobs obtained through formal mechanisms and networks, increases as network strength grows. Nevertheless, it is expected that in practice this principal prediction will continue to hold. The sample of immigrants is likely to have high discount rates, so that modest differences in the arrival rate of offers will not have large effects on the reservation wage, and these changes in the reservation wage will have still smaller effects on the expected wages obtained through each mechanism.

3 Empirical Framework

There are many candidates for measures of network size and strength. Our empirical strategy begins by verifying that the proposed measures of network strength and network size do predict network use. Having validated these measures in this way, we then ask whether or not these measures predict labor market outcomes. Finally, we examine whether network strength interacts with network use as predicted by the theoretical model.

Validating the Network Measures: We propose that network size be measured by the log of the share of working age population in the locality who are from the new immigrant's country of birth. Network strength is proxied by, whether or not the new immigrant had at least one close friend or relative in the locality when he just arrived. The latent tendency to find a job through the social network is given by,

$$NJ^*_{ijk} = \delta_1 F_{ijk} + \delta_2 S_{jk} + \beta X_{ijk} + \omega^1_j + \lambda^1_k + \varepsilon_{ijk} \tag{20}$$

where, F is a dummy variable for having at least one friend/relative in the locality upon arrival, S is the size variable, X is a set of additional controls that are likely to influence use of social networks in finding a job, and ω and λ are country of birth dummies and locality dummies. The subscripts i, j and k, refer to individual i, country of birth j, and locality k.

When the sample is limited to individuals with jobs, (20) is estimated by probit. When three choices (network job, formal job and unemployed) are allowed, a multinomial logit is used.

Network Structure: Once the network measures are validated, we regress labor market outcomes (time between arrival and first job, wage on first job, and difference in skills between first Canadian job and the job before migration) on the validated network measures, country of birth dummies, locality dummies, and other controls that are likely to affect labor market outcomes. This approach is given by,

$$Y_{ijk} = \alpha_1 F_{ijk} + \alpha_2 S_{jk} + \gamma X_{ijk} + \omega^2_j + \lambda^2_k + \upsilon_{ijk} \tag{21}$$

where Y is the relevant labor market outcome.

The model does not predict an unambiguous sign for the coefficients on network parameters in explaining unemployment duration but it does predict that workers with better networks will have higher wages.

In part, we carry out this estimation to permit comparison of results with the existing literature. The evidence on the effects of ethnic enclaves is mixed.[4] As mentioned in the introduction, there are arguments for both cases, namely that enclaves may benefit or hurt immigrants. Also, various studies may not have fully addressed the omitted variables bias issues that typically plague the estimation of network effects. Since we control for both location and country of birth, our network measures are unlikely to be correlated with location characteristics or group characteristics. Thus, α_2 is a *difference in differences estimator*. It is identified through variations in network size between, for example, Indians in Toronto and Indians in Ottawa, and comparing this difference with variations in network size between the Chinese across the same two cities. Bias of this form would arise only if Indian immigrants were more likely than Chinese immigrants to locate in Toronto, because the industrial structure of the city benefits Indians more than it does the Chinese immigrants. This cannot be ruled out completely, but our greater concern is that where the immigrant locates may tell us something about the immigrant: a Russian immigrant who locates where there are few established Russian immigrants, may be quite different from one who seeks out a Russian immigrant enclave. Nevertheless, this approach is useful because it is straightforward and addresses directly the effect of network structure on immigrant labor market outcomes.

Testing the Role of Networks: 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 validated measure of network strength. The equation above is augmented with an interaction between whether the individual found his first job through the social network, and whether he had at least one friend or relative in the locality when he first arrived.

$$W_{ijk} = \theta_1 F_{ijk} + \theta_2 S_{jk} + \theta_3 NJ_{ijk} + \theta_4 (NJ_{ijk} * F_{ijk}) + \pi X_{ijk} + \omega_j^3 + \lambda_k^3 + \zeta_{ijk} \tag{22}$$

where W is the wage in first job, and NJ is a dummy for whether the individual found his first job through the social network.

As explained in the theory section, when the immigrants' networks are stronger than formal channels (more likely to happen when they have a friend/relative close by), the effect of finding a job through the network should be negative, while when they are weaker, it should be positive. However, as mentioned earlier this result could also be due to other factors, such as, differing wage offer distributions from the two sources. It is not possible to know what drives the sign on θ_3. The testable implication of the model is that θ_4 is negative, that is the difference 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 (in other words the network premium), is decreasing in network strength.

An important advantage of this approach over the standard method of regressing labor market outcomes on measures of network structure, is that it mitigates problems associated with omitted variables. New immigrants are likely to share the unmeasured characteristics of

[4] Munshi (2003) and Edin, Fredriksson, and Aslund (2003) find that networks improve the labor market outcomes of Mexican immigrants to the United States and of refugees in Sweden. For three major cities in Canada, Hou and Picot (2003) find only a weak effect of exposure to own-group neighbours on immigrants' employment probability and annual earnings. In contrast, Lazear (1999) argues that immigrant enclaves reduce the rate at which immigrants learn the host-country language, while there is a large literature indicating that knowledge of host-country language raises wages (see Berman, Lang, and Siniver, 2003, and the references therein).

established immigrants. Thus, the outcomes of new and established immigrants are likely to be positively correlated even if there is no causal relation. Similarly, if a locality is especially conducive to good labor market outcomes for a particular immigrant group, this is likely to generate a positive correlation between the outcomes of new and established immigrants. In contrast, there is little reason to expect that, in areas where an immigrant group has a particular advantage, or where the group is particularly favorably selected, the bias will depend on the method through which the new immigrant finds a job. It is even less reasonable to anticipate that, the nature of the correlation is associated with the interaction of method of job finding and network strength. One would have to think of an unobservable that would affect the network-formal wage differential differently for those with and without strong social ties. The main motivation for including the interaction term comes from our theoretical model and the prediction that it have a significant negative sign in equilibrium. Thus, our main focus is to test the sign on θ_4.

4 Data and Descriptive Analysis

4.1 Data

We use a 20% 2001 Census of Canada sample to calculate characteristics of immigrant populations by country of origin and location within Canada. The sample is restricted to the working age population (those between 24 and 64 years old). According to the 2001 Census, immigrants constitute 18 percent of the Canadian population, and 21 percent of the labor force. They come from more than 200 source countries. Source countries with fewer than 500 immigrants in the census sample are dropped, so that there are sufficient observations in each cell to calculate network measures with reasonable precision. The geographical unit used to characterize local networks is the Census Metropolitan Area, CMA, or the Census Agglomeration, CA[5] Using the 2001 Census, we calculate the share of working age population in each CMA/CA from each source country, which is our measure of network size. Measures of the wage distribution of the employed immigrant population from a particular country, residing in a particular CMA/CA, 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 sample consists of immigrants who arrived in Canada between October 1, 2000 and September 30, 2001, and were 15 years or older. This population is referred to as *recent immigrants*. The LSIC is a longitudinal survey with three waves: six months, two years and four years, since arrival in Canada. It provides data on the recent immigrant's characteristics, such as, sex, age, education, languages spoken, country of birth and geographic location in Canada, and also his job history, which includes labor force status, weekly wage if employed, etc. The sample is restricted to those of working age, who are in the labor force. In the first wave, 74 percent of this age group were in the labor force. Individuals whose first job was arranged

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

before they migrated to Canada, or who were either self employed, or in a family business[6] are dropped. Recent immigrants who move across CMA/CAs are also excluded.[7] Observations from CMA/CAs and from source countries with fewer than 10 immigrants in the LSIC sample, and from source countries that are dropped from the census sample, are also excluded. The final wave one *LSIC sample* consists of 5123 recent immigrants, from 53 different source countries and residing in 16 different CMA/CAs across Canada.[8]

4.2 Descriptive Analysis

Although we drop a large number of countries and localities, the largest sending countries, and the largest receiving localities, account for the vast majority of immigrants. The first two columns of Table 1 show the twenty countries that have the largest shares of working age immigrant population in Canada according to the 2001 Census. The top twenty source countries constitute 68% of the working age immigrant population. Recent immigrants from the above countries are more likely to have large social networks. Columns three and four show the same information, but restrict the sample to immigrants who arrived after 1995. The last two columns show the countries that contributed the largest inflow of working age immigrants as measured by the first wave of the LSIC. Together, these countries account for 78% of working age immigrants arriving during this period. The table reveals the well-documented increase in the share of immigrants from Asia, and the decline in the share from Europe.

Table 2 shows that, the five largest CMAs (Toronto, Montreal, Vancouver, Ottawa, Calgary) have 52 percent of Canada's working-age population, 75 percent of its working-age immigrants and 83 percent of its recent working-age immigrants. Thus, recent immigrants are settling in areas were there is an already large concentration of immigrants. For the three largest source countries of recent immigrants, Table 3 shows the tendency of recent immigrants to settle in areas with a large population of immigrants from their own country.

Table 4 shows the means for the variables in the first wave of the LSIC. By the time of the first wave, 69 percent of the sample had held a first job. Of these, 42 percent reported that *they found this job through a friend or relative, which is defined as a network job.* The remainder used other methods, such as, contacting the employer directly, responding to newspaper advertisements, employment agencies, the internet, referral from another employer or a union. These are referred to as formal jobs.

We proxy network strength by a binary variable. It takes the value 1, if the individual reports that he already had at least one relative or friend in the city where he resides, when he first arrived in Canada. While 89 percent had at least one relative or friend in Canada on arrival, 82 percent have one in the city where they reside. By this measure, most recent

[6] In the first wave of the LSIC, 8.5 percent of the recent immigrants in the labor force are in pre-arranged jobs. 2.6 percent report being self-employed and 0.6 percent report being involved in a family business, when asked about their first jobs.

[7] A mover is dropped because it is not clear whether one should consider his network to be the relevant group in the new location or in the old one. For example it could be the case that a person's network in his previous location helped him find a job in his current location. In this case, it would be incorrect to characterise the relevant group at the current/interview location as his social network. In order to simplify matters and present clean results movers are excluded from the sample. At the time of the first wave, 7.7 percent of recent immigrants in the labour force have moved across CMA/CAs and are therefore dropped.

[8] Of the 16 CMA/CAs only one (Guelph) is a CA. Therefore, henceforth they will be referred to as CMAs.

immigrants have strong networks.

We capture the size of the recent immigrant's network by the natural logarithm of the share of working age CMA population from his country of birth. Note that, since CMA dummies are included, this is isomorphic to including the natural logarithm of the number of immigrants from his country of birth.

Two things must be noted at this point. First, finding the first job through the social network does not necessarily imply the presence of a relative or friend in the same city of residence on arrival. Immigrants may have found their first job through a friend made after migrating to Canada, a relative or friend elsewhere, or through a compatriot who is not a relative or friend known previously. Thus, having a network job does not imply having a strong network. 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 correlated. 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. having a network job) is not perfect.

5 Results

5.1 Validating the Network Measures

Table 5 shows the relation between, the recent immigrant's use of networks in finding the first job within six months (network job), and, the presence upon arrival of at least one friend or relative in his locality (network strength). The first column shows that immigrants who have at least one close friend or relative in their locality upon arrival are sixteen percentage points more likely to find their first job through a network than are other immigrants. Controlling for the percentage of established immigrants in the CMA from the person's country of birth (network size) has no effect (column (2)).

Column (3) controls for a large number of potential confounding factors, including locality and country of birth. It shows that, conditional on having a job, the probability of having a network job is 11 percentage points higher among those who had a friend or relative on arrival, and does not show evidence of an effect of network size.

It is possible, although to us implausible, that strong ties increase the fraction of network jobs among the employed by reducing the probability of a formal job and increasing the probability of unemployment rather than by increasing the probability of holding a network job. Therefore, in column (4) the sample is expanded to include those who have not found a job within six months of arrival. Network strength continues to have a strong effect, and now size has a positive effect as well, suggesting that network size influences job finding. In column (5), the dependent variable is "have a job." Here network size has a clear effect, but strength does not. Columns (4) and (5) together suggest that strong ties largely substitute network jobs for formal jobs.

To address this more directly, in columns (6) and (7), we present the results of a multinomial logit, where the three outcomes are, having a formal job (FJ), having a network job (NJ), and the base category of being unemployed. Strength contributes to finding a network job, while size contributes to finding both types of jobs. Thus, table 5 validates the two network variables as measures of the influence of networks in finding first jobs.

Tables 6 and 7 replicate the exercise in table 5, but look at the relation between finding a network job and network strength, for first jobs found within two years and four years, respectively.[9] Once again, the presence of a relative or friend, is revealed as a good measure of network influence in finding jobs. These tables also reveal that, recent immigrants with a high school or lower level of education are more likely to find their first jobs using networks, while those with a university degree are less likely to use networks to do so (reference category being immigrants with a college certificate). This conforms to the notion that the low skilled workers use networks much more than high skilled workers do.[10] Surprisingly the tables also show that university graduates are less likely to be employed. This could be because of more competition among highly educated immigrants in the labor market.[11] Also, immigrants fluent in English are less likely to use networks in finding their first jobs.

5.2 Importance of Network Measures over time

Section 5.1 validates the network measures of size and strength as good predictors of the use of networks in finding first jobs. At the six month interview, conditional on employment, 42 percent of the recent immigrants report that they found their *current or most recent job* using networks. Again, conditional on employment, at the two year interview this figure is 41 percent, and at the four year interview it is 39 percent. Recent immigrants continue to use networks to find jobs even after staying for four years in Canada. One question that comes to mind is whether or not the network measures of size and strength continue to predict network use over time.

Tables 8, 9 and 10 look at the current or most recent job at each interview, and replicate tables 5, 6 and 7 respectively. Table 8 very closely resembles table 5. This is not surprising because 87 percent of the current or most recent jobs, at the six month interview, were also the first jobs. As in the case of first jobs, the presence of at least one close friend or relative in the locality, predicts the use of networks in finding the most recent job. The multinomial logit results in column (5) show that the probability of finding the current or most recent job using the network is higher for those having a strong network. As in the case of first jobs, a larger network size helps in finding both formal and network jobs. Table 9 finds similar evidence for the importance of network strength in predicting the use of networks at the two year interview. Finally, table 10 shows that, at the four year interview, both the measures of network are no longer significant in explaining the use of networks in finding jobs. However

[9] Statistics Canada estimates that in each wave less than 2 percent of the LSIC sample is no longer eligible because sample members have either left Canada, died or been institutionalized. This allows us to add first jobs obtained after the first wave to the wave one sample of first jobs without disrupting the nationally representative character of the LSIC sample of recent immigrants.

[10] Departure from this conventional notion is examined in Saxenian (1999). The paper examines the extent to which the skilled Chinese and Indian immigrants are organizing ethnic networks in California's Silicon Valley to support the often risky process of starting new technology businesses. The author notes that Silicon Valley's new immigrant entrepreneurs are more highly skilled than their counterparts in traditional industries, but like those counterparts they have created a rich fabric of professional and associational activities that facilitate immigrant job search, information exchange, access to capital and managerial know-how and the creation of shared ethnic identities.

[11] As table 4 shows, 70 percent of recent immigrants in our sample hold a university degree. Thus, most Canadian immigrants today are highly educated. They may be competing for jobs amongst themselves, especially as finding good job matches takes longer for highly skilled workers.

because of attrition between waves, the sample size declines dramatically from one wave to the next. The coefficients may be losing significance because of smaller sample size.

To check if smaller sample size is driving the results for current/recent jobs at the four year interview, we carry out a robustness check by restricting the sample at the earlier interviews (six months and two years) to only those present at the four year interview (results not shown here). Network strength continues to predict finding current/recent jobs using networks at the six month and two year interviews, even when the sample is restricted as stated. Thus, it seems to be the case that the measures of network structure used here do not effectively capture network influence in finding jobs during the third wave between two and four years since arrival. This would be the case if the nature of networks changes with time spent in the host country. This is likely to happen as the immigrant builds new friendships in the host country.

5.3 Time to First Job

Table 11 shows the results from censored normal regressions for unemployment duration, or equivalently, time between arrival and finding the first job. A larger network is associated with shorter unemployment duration: a ten percent increase in the share of the recent immigrant's country of birth population in total CMA working age population[12] reduces unemployment duration by about 1.6 percent. Given a median unemployment duration of 115 days[13] at six months, this translates to a reduction of less than two days. The covariates show some interesting results. In the first six months, being female increases search time to first job by almost 25 percent, and being married increases it by 10 percent. Unemployment duration is reduced by 28 percent if the immigrant lived in Canada previously (as a non-tourist), and it is increased by 47 percent if he is a refugee. Finally having a high school or lower level of education reduces search time by 24 percent. This could be because of lower competition for low skill jobs as compared to jobs requiring higher levels of education.

5.4 Network Structure and Wages

Column (1) of table 12 presents the results of an OLS (difference in differences) wage regression with the network measures. It reveals a small negative and statistically insignificant effect of network size on earnings. This is consistent with larger networks being associated with a faster arrival rate of offers (given the effect on unemployment duration found in table 11), but with either little or no effect on the reservation wage, or increasing the arrival rate at the lower end of the wage distribution.

The presence of at least one relative or friend in the locality on arrival (network strength) enters with the right sign, and has a nontrivial point estimate (over 5 percent), but does not reach statistically significance at conventional levels.

[12] According to the 1996 census, the shares from China, India and Philippines, in Toronto's working age population were, 2.4 percent, 3.2 percent, and 2.5 percent, respectively. In 2001, these shares changed to, 3.4 percent, 4.2 percent, and 2.5 percent, respectively; representing a 39 percent, 33 percent, and 17 percent change, in shares from China, India and Philippines, in Toronto's working age population.

[13] In calculating this figure, recent immigrants who had not yet found a job since arrival, were given an unemployment duration of 6 months, and were included in the calculation of the median. Also note that, 69% of recent immigrants in the labor force were employed within six months since arrival.

This finding of an insignificant effect of network size on earnings is consistent with previous findings for Canada. Hou and Picot (2003) examine the association between living in a visible minority enclave and immigrants' labor market outcomes in Canada's three largest cities and also find little association between exposure to own-group neighbors and immigrants' annual earnings. Since controls for language are included here, these results are not directly comparable to Lazear (1999) in the United States, but they do not confirm an adverse effect of ethnic enclaves. As discussed before, there are some endogeneity concerns that are not addressed by the approach in table 12. Therefore, it is not clear whether these results differ from Edin, Fredriksson, and Aslund (2003) because of differences in the nature of immigrants to Sweden and Canada, or because of differences in approach.

The remaining columns present the results of quantile estimates. 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. 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.

Columns (2) - (4) present quantile regression results for wages, conditional on having a wage. The results are similar to those obtained using OLS, although there is some evidence of an even larger effect of network strength on initial wages at the 25th percentile, and this effect is statistically significant at 0.1 level. A strong network results in a 9.4 percent increase in wages in first jobs at the 25th percentile of an individual's accepted wage offer distribution.[14] Columns (5) and (6) also include the unemployed immigrants (who are in the labor force) by assigning them very low wages. It is not possible to estimate the model for the 25th percentile because a high proportion of new immigrants are unemployed. There is continued weak evidence of a positive effect of network strength on wages, in that the coefficients are statistically, but not numerically, insignificant. The analysis is extended to include individuals who found their first job after six months up to four years (tables 13 and 14). The results are broadly similar. The effect of network strength is positive and statistically significant at conventional levels for the 25th percentile of wages in first jobs (conditional on having a job) obtained during the two year and four year periods.

However, as discussed above, the network structure approach is limited by the concern that individuals who locate near friends or family, or in areas where their are an unusually large number of established immigrants from their country of birth, differ in unmeasured ways from those who do not.[15] Therefore, the paper turns to testing the prediction of the theoretical model.

[14] Because there are controls for education the quantile regression results need to be interpreted carefully. The positive effect of a stronger network does not bump up an individual's position in the unconditional population wage distribution, but results in a higher paying job at the 25th percentile of his conditional wage offer distribution.

[15] Endogeneity of locating close to a friend or relative conditional on having one, does not seem to be a serious problem. Fully 92 percent of the recent immigrants who had at least one relative or friend in Canada chose to live close to their ties. One cannot completely rule out the possibility that individuals who choose to move to Canada without having a friend or relative present are different from other immigrants. However, we control for the presence of a relative or friend in Canada but not in the same locality as the recent immigrant. Such immigrants do not differ from those who do not have a tie in Canada.

5.5 Augmented Wage Model

Table 15 shows the results for the wage equation with the method of finding the first job (whether or not it was found using the network) and the interaction between this variable and network strength included in the regression.[16] It is easy to tell stories in which the use of a network is positively or negatively correlated with unobserved worker characteristics, but less easy to explain why this correlation should be noticeably different for those with and without strong networks. Therefore, the paper's primary focus is on the interaction term.

Column (1) shows that among those who did not have a friend or relative when they first arrived at their locality in Canada, finding a job through a network is associated with a trivial and statistically insignificant 0.2 percent lower wage. In contrast, among those with a friend or relative, the wage penalty associated with finding a job through a network is about 3.2 percentage points higher although again not statistically significant.

Columns (2)-(4) present quantile regressions for the 25th, 50th and 75th quantiles. As in earlier tables, only the standard error for network size is adjusted for clustering. Only 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.

At the 25th percentile, among recent immigrants in formal jobs, those who have at least one strong social tie in their locality earn a wage that is 12.8 percent higher compared to those who do not have strong social ties. Again at this lower end of the individual wage distribution, those with strong social tie(s) and in network jobs earn 13.6 (12.8+17.2-16.4) percent higher wages compared to the omitted group of immigrants without strong social ties and in formal jobs.

Also at the 25th percentile, in the absence of strong networks (strong social ties), those finding their first jobs through networks have weekly wages that are 17.2 percent higher than those doing so using formal means. In other words, at the lower end of the wage distribution, among recent immigrants who do not have a strong social tie in their locality upon arrival, those who are in network jobs earn a wage that is 17.2 percent higher compared to those who obtained jobs through formal channels. The model predicts this difference if networks are less likely to relay job offers than are formal methods (more likely to happen in the absence of a relative or friend close by). However, as mentioned earlier, this finding is also consistent with other explanations such as unobserved differences between network users and non-users, or differences between the network and formal wage offer distributions. More importantly, as predicted by the model, the coefficient on the interaction term is negative and statistically significant. For those who have a strong social tie, those who are in network jobs earn a wage that in only 0.8 percent higher (17.2-16.4) compared to those who obtained jobs through formal channels. In other words, for those who have at least one relative or friend in their locality, the network premium (network-formal wage differential) is 16.4 percent lower (network premium for those with strong networks is 0.8 percent) compared to the network premium for immigrants without strong networks (network premium for those without strong networks is 17.2 percent). Therefore the network premium is decreasing in network strength

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

as predicted by the theoretical model. The estimates are replicated by adding in workers who found their first job after six months but within four years. As seen in tables 16 and 17, the interaction term continues to be negative and significant albeit only at the .1 level in table 17.[17]

5.6 Skill in First Jobs

The LSIC asked recent immigrants about their occupation before coming to Canada. Those without jobs were asked about their intended occupation in Canada. The LSIC reports an associated skill level based on the National Occupation Classification (NOC), which determines skill level by the type and/or amount of training or education required for the work. It also records respondents' first post-immigration occupation using the 1991 Standard Occupation Classification Code (SOC). We established a concordance between the NOC and SOC codes, which makes it possible to obtain the skill levels in the immigrant's job just before migration, and in his first job in Canada. About two-thirds of the sample pre-immigration or planned jobs required the highest skill level. Of these, among those finding jobs within six months, 73 percent took an initial Canadian job requiring a lower skill level. This raises concerns about whether immigrant human capital is underutilized, and whether networks affect the probability of such underutilization.

Table 18 presents probit estimates of the determinants of having a job with an appropriate skill level for highly skilled immigrants who found a job in Canada within six months, two years, and four years of arrival. The dependent variable takes the value 1 when the first job is in the highest skill category and 0 otherwise. Network size and network strength do not affect the probability of the first job being a highest skill job. As might be expected, for these high-skill immigrants, being fluent in English, having lived in Canada before as a non-tourist, having an economic visa and being the principal applicant (as opposed to the dependent) raise the probability of the first job in Canada being at the highest skill level.

If network and formal jobs are drawn from the same skill distribution, then the model would produce results for skill similar to those obtained for wages. In table 19, the specification in table 18 is augmented with job finding method and the interaction between job finding method and network strength. Compared to those finding jobs using formal means, those finding their first jobs through networks are more likely to be in jobs which underutilize their skills. Network strength does not affect this result. This is consistent with the earlier finding that, the principal effect of networks is to provide access to jobs at the lower end of the individual's wage (or skill) distribution.

6 Summary

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. The model shows that among immigrants with networks that are stronger than formal channels,

[17] We also examined the network effect on wages by restricting the analysis to various sub-samples, according to gender and education and to immigrants who belonged to countries where English was *not* the lingua franca. The results were not demonstrably different and no interesting patterns across sub-groups were observed, possibly because standard errors get too large when sub-samples are used.

those who are in network jobs have lower wages than those in formal jobs. It also predicts that the network-formal wage differential is decreasing in network strength. These implications were tested using data on a nationally representative sample of recent immigrants into Canada. The empirical strategy to carry out comparative statics, augments the difference in differences framework with an interaction term between network strength and finding a network job, and focuses on the coefficient of this interaction term. This strategy has an important advantage over the standard method of regressing labor market outcomes on measures of network influence, in that it mitigates problems associated with omitted variables. The model's prediction is not rejected in any of the specifications, and is strongly supported for wages at the lower end of an individual's acceptable wage distribution. This suggests that the presence of at least one strong social tie in the recent immigrant's immediate neighborhood upon his arrival increases the number of offers he receives from the network, at least at this end of the his acceptable wage distribution.

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 strong social ties in their localities enjoy a faster arrival rate of jobs, at least at the lower end of their wage distribution. Our paper does not address other issues related to immigrant dispersion, including the longer term labor market effects of immigrant enclaves.

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A Appendix of Tables

Table 1: Working Age Immigrants by Country of Birth, Top 20

Source Country	Percent Immigrant Population Census 2001	Source Country	Percent Immigrant Population after 1995 Census 2001	Source Country	Percent Recent Immigrant Population LSIC, Wave1
U.K.	9.73	China	15.00	China	21.65
India	6.77	India	10.67	India	15.03
China	6.15	Philippines	6.13	Philippines	6.87
Italy	5.48	Pakistan	4.19	Pakistan	4.81
Philippines	4.96	Hong Kong	3.82	South Korea	4.41
Hong Kong	4.82	Iran	3.34	Romania	3.02
United States	3.43	Taiwan	2.89	Iran	2.50
Vietnam	3.40	South Korea	2.78	Russian Fd.	2.23
Portugal	3.30	Sri Lanka	2.76	Morocco	1.97
Poland	2.95	Russian Fed.	2.62	Algeria	1.96
Jamaica	2.60	Romania	2.37	Sri Lanka	1.93
Germany	2.49	U.K.	1.82	France	1.74
Guyana	1.84	Yugoslavia	1.75	Bangladesh	1.60
Sri Lanka	1.78	Ukraine	1.72	U.K.	1.60
Pakistan	1.48	United States	1.65	Ukraine	1.42
Netherlands	1.48	France	1.52	Afghanistan	1.16
Greece	1.43	Bosnia Herz.	1.44	United States	1.05
Lebanon	1.42	Algeria	1.37	Lebanon	1.01
TrinidadTobago	1.42	Bangladesh	1.33	Colombia	1.00
Iran	1.41	Vietnam	1.32	Iraq	0.99
Total	68.34	Total	70.49	Total	77.95

Table 2: CMA of Residence, Working Age Population, Top 5

CMA	Percent Total Population Census 2001	CMA	Percent Immigrant Population Census 2001	CMA	Percent Immigrant Population, after 1995 Census 2001	CMA	Percent Recent Immigrants LSIC, Wave1
Toronto	20.04	Toronto	40.69	Toronto	44.61	Toronto	46.35
Montreal	14.62	Vancouver	14.49	Vancouver	18.20	Vancouver	14.43
Vancouver	8.63	Montreal	12.18	Montreal	12.75	Montreal	13.79
Ottawa	4.59	Calgary	4.03	Ottawa	4.08	Calgary	4.59
Calgary	4.15	Ottawa	3.65	Calgary	3.92	Ottawa	3.75
Total	52.03	Total	75.04	Total	83.56	Total	82.90

Table 3: CMA of Residence, Working Age Immigrants

	Chinese		Indians		Philippines	
CMA	Census[1]	LSIC[2]	Census[1]	LSIC[2]	Census[1]	LSIC[2]
Toronto	41.72	48.68	47.12	61.70	44.66	46.72
Vancouver	30.69	21.97	21.90	12.45	19.89	23.50
Montreal	6.51	11.12	4.50		5.95	
Calgary	4.43	3.74	4.19	4.60	5.35	5.71
Ottawa	4.41	4.69				
Abbotsford			3.54	2.90		
Winnipeg					8.82	6.78
Edmonton				3.08		4.33

1. Census data refers to all immigrants from the relevant country
2. LSIC data refers to recent immigrants from the relevant country

Table 4: Description of Variables, LSIC Wave1

Variable	Description	Mean (Fraction)	Obs.
	Dependent Variables		
Network Job	1= Found first job using Network	0.29	5362
	0= (No job) or (Found first job using Formal Sources)		
Network Job | Have a Job	1= Found first job using a network, conditional on having a job	0.42	3705
	0= Found first job using formal sources, conditional on having a job		
Have a Job	1= Have a job	0.69	5362
	0= Never had a job		
Weekly Wage		408.14	3562
Weekly Wage	Median	350	3562
Duration till first Job	Median (in days)	115	5362
	Main Explanatory Variables		
Network Strength	1= At least 1 relative/friend present close by on arrival	0.82	5362
	0= No relative/friend present close by on arrival		
Relative/friend in Canada	1= At least 1 relative/friend present in Canada on arrival	0.89	5362
	0= No relative/friend present in Canada on arrival		
Relative/friend in Canada	1=Atleast 1 relative/friend in Canada on arrival	0.07	5362
and none close by	and no relative/friend close by on arrival		
	0= No relative/friend present in Canada on arrival		
	or At least 1 relative/friend present close by on arrival		
Network Size	Share working age pop. in CMA/CA having same country of birth	0.02	5362
	Std. dev	[0.018]	
	Min	0.00003	
	Max	0.109	
	Control Variables		
Sex	1=Female, 0=Male	0.42	5362
Age	In years	35.48	5362
Married	1=Yes, 0 otherwise	0.83	5362
Kids		0.94	5362
Speak English well	1=Yes, 0 otherwise	0.65	5362
Speak French well	1=Yes, 0 otherwise	0.12	5362
Lived Before in Canada	1=Yes, 0 otherwise	0.06	562
(not as a tourist)			
Sponsored by family member	1=Yes, 0 otherwise	0.24	5362
Principal Applicant	1=Yes, 0 Spouse or Dependant	0.72	5362
Visa Category			
Economic visa class	Reference category	0.77	5310

Table 4: Description of Variables, LSIC Wave1

Variable	Description	Mean (Fraction)	Obs.
Family visa class	1=Yes, 0 otherwise	0.21	5310
Refugee visa class	1=Yes, 0 otherwise	0.03	5310
Education Category			
High sch. or less	1=Yes, 0 otherwise	0.14	5332
Some university (no degree)	Reference category	0.16	5332
University degree, Doctrate	1=Yes, 0 otherwise	0.7	5332
Occupation before migration			
Managers	Reference category	0.02	5316
Professionals	1=Yes, 0 otherwise	0.39	5316
Paraprofessionals	1=Yes, 0 otherwise	0.15	5316
Clerks	1=Yes, 0 otherwise	0.03	5316
Labourers	1=Yes, 0 otherwise	0.002	5316
Students	1=Yes, 0 otherwise	0.02	5316
New workers	1=Yes, 0 otherwise	0.25	5316
None	1=Yes, 0 otherwise	0.15	5316

Using LSIC analysis sample except includes recent immigrants from CMA/CAs and countries with less than 10 immigrants in LSIC.

Table5: Network influence in finding first jobs within first six months

	Probit Marginal Effects					Multinomial Logit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NJ|HJ	NJ|HJ	NJ|HJ	NJ	HJ	FJ	NJ
Network Size		0.007	0.032	0.042***	0.050***	0.180**	0.320***
		[0.014]	[0.021]	[0.016]	[0.014]	[0.074]	[0.090]
Network Strength	0.164***	0.164***	0.114***	0.093***	0.025	-0.073	0.473**
	[0.021]	[0.021]	[0.027]	[0.024]	[0.026]	[0.107]	[0.187]
Relative/Friend not close by			-0.003	-0.007	-0.013	-0.069	-0.060
			[0.039]	[0.036]	[0.039]	[0.168]	[0.270]
Female			-0.060**	-0.068***	-0.075***	-0.247**	-0.497***
			[0.026]	[0.019]	[0.020]	[0.107]	[0.122]
Age			0.003	-0.001	-0.007***	-0.039***	-0.029***
			[0.002]	[0.002]	[0.001]	[0.005]	[0.009]
Married			-0.053**	-0.036**	-0.017	0.028	-0.165
			[0.023]	[0.018]	[0.022]	[0.115]	[0.128]
Kids			0.031***	0.020***	-0.002	-0.063	0.064
			[0.010]	[0.007]	[0.007]	[0.044]	[0.039]
High school or less[1]			0.104**	0.091***	0.068***	0.073	0.463***
			[0.049]	[0.034]	[0.026]	[0.184]	[0.160]
University degree[1]			-0.034	-0.042**	-0.038**	-0.122	-0.281***
			[0.025]	[0.018]	[0.015]	[0.089]	[0.095]
Speak English well			-0.097***	-0.067***	-0.017	0.077	-0.299***
			[0.026]	[0.019]	[0.017]	[0.095]	[0.107]
Speak French well			-0.124***	-0.051	0.028	0.298	-0.169
			[0.047]	[0.034]	[0.039]	[0.209]	[0.244]
Lived in Canada Before			-0.046	-0.021	0.046	0.298	0.068
			[0.051]	[0.036]	[0.032]	[0.187]	[0.233]
Principal Applicant			-0.020	-0.019	0.027	0.225	0.022
			[0.030]	[0.022]	[0.029]	[0.158]	[0.151]
Sponsored by family			0.001	0.016	-0.004	-0.110	0.043
			[0.046]	[0.036]	[0.039]	[0.192]	[0.233]
Family Visa[2]			0.137**	0.067	-0.065	-0.563**	-0.021
			[0.063]	[0.052]	[0.058]	[0.275]	[0.322]
Refugee Visa[2]			0.174**	0.073	-0.108	-1.007**	-0.130
			[0.079]	[0.056]	[0.073]	[0.392]	[0.325]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3524	3524	3437	4959	4982	4982	
Log Pseudolikelihood[3]	-2373.23	-2372.60	-2086.91	-2701.53	-2762.83	-4845.83	
Clusters	326.00	326.00	318.00	380.00	383.00	383.00	

Robust standard errors corrected for group effects within CMA/CA-country cells in brackets;
* significant at 10%; ** significant at 5%; *** significant at 1%;
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class
3 The word "pseudolikelihood" instead of likelihood is to stress the point that by specifying the -cluster- option we no longer have independent observations but rather independent clusters
NJ: Network Job, HJ: Have a Job, FJ: Formal Job

Table6: Network influence in finding first jobs within first two years

	Probit Marginal Effects			Multinomial Logit	
	(1)	(2)	(3)	(4)	(5)
	NJ|HJ	NJ	HJ	FJ	NJ
Network Size	0.024	0.039**	0.033***	0.198**	0.313***
	[0.019]	[0.017]	[0.010]	[0.079]	[0.095]
Network Strength	0.107***	0.106***	0.023	-0.019	0.512***
	[0.023]	[0.023]	[0.019]	[0.125]	[0.182]
Relative/Friend not close by	0.003	0.008	-0.005	-0.043	0.022
	[0.032]	[0.033]	[0.029]	[0.211]	[0.272]
Female	-0.043*	-0.050**	-0.028*	-0.120	-0.321**
	[0.024]	[0.023]	[0.016]	[0.115]	[0.156]
Age	0.002	-0.001	-0.005***	-0.040***	-0.035***
	[0.002]	[0.001]	[0.001]	[0.007]	[0.008]
Married	-0.042*	-0.037*	-0.005	0.053	-0.124
	[0.023]	[0.021]	[0.016]	[0.127]	[0.147]
Kids	0.024**	0.022***	0.002	-0.036	0.073
	[0.010]	[0.008]	[0.007]	[0.059]	[0.056]
High school or less[1]	0.131***	0.116***	0.031	-0.106	0.422**
	[0.049]	[0.041]	[0.022]	[0.235]	[0.214]
University degree[1]	-0.037*	-0.052**	-0.045***	-0.297**	-0.454***
	[0.022]	[0.021]	[0.015]	[0.138]	[0.142]
Speak English well	-0.094***	-0.075***	-0.003	0.144	-0.242**
	[0.021]	[0.017]	[0.014]	[0.127]	[0.122]
Speak French well	-0.080*	-0.038	0.024	0.284	-0.012
	[0.042]	[0.037]	[0.025]	[0.215]	[0.257]
Lived in Canada Before	-0.040	-0.032	0.020	0.255	0.035
	[0.046]	[0.039]	[0.026]	[0.235]	[0.270]
Principal Applicant	-0.023	-0.026	0.006	0.124	-0.034
	[0.029]	[0.026]	[0.023]	[0.193]	[0.205]
Sponsored by family	0.042	0.062	0.038	0.231	0.466*
	[0.040]	[0.038]	[0.026]	[0.238]	[0.277]
Family Visa[2]	0.077	0.026	-0.095**	-0.831***	-0.514
	[0.056]	[0.050]	[0.046]	[0.307]	[0.344]
Refugee Visa[2]	0.178**	0.123**	-0.063	-0.908**	-0.076
	[0.072]	[0.063]	[0.059]	[0.434]	[0.387]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes
Observations	4122	4959	4950	4982	
Log Pseudolikelihood[3]	-2507.72	-2886.17	-2032.66	-4533.34	
Clusters	353.00	380.00	369.00	383.00	

Robust standard errors corrected for group effects within CMA/CA-country cells in brackets;
* significant at 10%; ** significant at 5%; *** significant at 1%;
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class
3 The word "pseudolikelihood" instead of likelihood is to stress the point that by specifying the -cluster- option we no longer have independent observations but rather independent clusters.
NJ: Network Job, HJ: Have a Job, FJ: Formal Job

Table7: Network influence in finding first jobs within first four years

	Probit Marginal Effects			Multinomial Logit	
	(1)	(2)	(3)	(4)	(5)
	NJ	NJ and HJ	HJ	FJ	NJ
Network Size	0.020	0.031*	0.022**	0.147	0.246**
	[0.018]	[0.017]	[0.009]	[0.090]	[0.101]
Network Strength	0.092***	0.092***	0.018	-0.000	0.442***
	[0.022]	[0.021]	[0.015]	[0.119]	[0.170]
Relative/Friend not close by	-0.005	-0.005	-0.010	-0.082	-0.071
	[0.030]	[0.028]	[0.023]	[0.192]	[0.228]
Female	-0.044*	-0.049**	-0.019	-0.070	-0.279*
	[0.023]	[0.022]	[0.014]	[0.124]	[0.151]
Age	0.002	-0.001	-0.004***	-0.043***	-0.038***
	[0.002]	[0.001]	[0.001]	[0.007]	[0.007]
Married	-0.043*	-0.032	0.009	0.175	-0.006
	[0.024]	[0.022]	[0.017]	[0.153]	[0.163]
Kids	0.023**	0.022***	0.002	-0.025	0.081
	[0.010]	[0.008]	[0.006]	[0.066]	[0.060]
High school or less[1]	0.132***	0.115***	0.025	-0.136	0.393*
	[0.047]	[0.042]	[0.020]	[0.238]	[0.233]
University degree[1]	-0.037*	-0.045**	-0.024*	-0.159	-0.316**
	[0.022]	[0.020]	[0.015]	[0.156]	[0.153]
Speak English well	-0.096***	-0.084***	-0.015	0.042	-0.350***
	[0.019]	[0.017]	[0.010]	[0.105]	[0.108]
Speak French well	-0.036	-0.011	0.008	0.110	0.003
	[0.044]	[0.037]	[0.023]	[0.231]	[0.241]
Lived in Canada Before	-0.030	-0.020	0.014	0.166	0.042
	[0.045]	[0.039]	[0.021]	[0.219]	[0.252]
Principal Applicant	-0.031	-0.038	-0.007	-0.000	-0.171
	[0.028]	[0.026]	[0.019]	[0.196]	[0.204]
Sponsored by family	0.041	0.062*	0.044*	0.365	0.576*
	[0.039]	[0.037]	[0.026]	[0.301]	[0.329]
Family Visa[2]	0.078	0.028	-0.104**	-0.966***	-0.634
	[0.054]	[0.050]	[0.049]	[0.363]	[0.401]
Refugee Visa[2]	0.181***	0.139**	-0.060	-0.903**	-0.066
	[0.067]	[0.060]	[0.054]	[0.435]	[0.397]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes
Observations	4274	4982	4950	4982	
Log Pseudolikelihood[3]	-2604.39	-2932.40	-1854.40	-4452.69	
Clusters	359.00	383.00	369.00	383.00	

Robust standard errors corrected for group effects within CMA/CA-country cells in brackets;
* significant at 10%; ** significant at 5%; *** significant at 1%;
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class
3 The word "pseudolikelihood" instead of likelihood is to stress the point that by specifying the -cluster- option we no longer have independent observations but rather independent clusters
NJ: Network Job, HJ: Have a Job, FJ: Formal Job

Table 8: Network influence in finding current/most recent job, at 6 month interview

	Probit Marginal Effects			Multinomial Logit	
	(1)	(2)	(3)	(4)	(5)
	NJ|HJ	NJ	HJ	FJ	NJ
Network Size	0.023	0.037**	0.050***	0.196***	0.297***
	[0.023]	[0.017]	[0.014]	[0.074]	[0.090]
Network Strength	0.112***	0.092***	0.025	-0.072	0.468**
	[0.029]	[0.025]	[0.025]	[0.101]	[0.192]
Relative/Friend not close by	0.003	-0.002	-0.015	-0.086	-0.044
	[0.040]	[0.037]	[0.039]	[0.166]	[0.265]
Female	-0.037	-0.053***	-0.075***	-0.282**	-0.439***
	[0.024]	[0.018]	[0.019]	[0.110]	[0.110]
Age	0.003*	-0.001	-0.007***	-0.039***	-0.027***
	[0.002]	[0.002]	[0.001]	[0.005]	[0.009]
Married	-0.038	-0.026	-0.012	0.027	-0.11
	[0.024]	[0.017]	[0.021]	[0.119]	[0.111]
Kids	0.026***	0.017**	-0.002	-0.056	0.052
	[0.009]	[0.007]	[0.008]	[0.044]	[0.039]
High school or less[1]	0.088**	0.084***	0.067**	0.104	0.445***
	[0.044]	[0.031]	[0.027]	[0.183]	[0.159]
University degree[1]	-0.037	-0.043**	-0.039***	-0.126	-0.284***
	[0.023]	[0.017]	[0.015]	[0.089]	[0.092]
Speak English well	-0.103***	-0.073***	-0.016	0.097	-0.312***
	[0.027]	[0.020]	[0.017]	[0.097]	[0.109]
Speak French well	-0.118**	-0.047	0.026	0.274	-0.145
	[0.048]	[0.036]	[0.041]	[0.216]	[0.243]
Lived in Canada Before	-0.013	0.002	0.054*	0.300*	0.204
	[0.048]	[0.036]	[0.032]	[0.182]	[0.229]
Principal Applicant	0.003	-0.001	0.032	0.2	0.104
	[0.032]	[0.023]	[0.029]	[0.166]	[0.148]
Sponsored by family	0.012	0.024	-0.002	-0.127	0.076
	[0.050]	[0.039]	[0.039]	[0.185]	[0.237]
Family Visa[2]	0.115	0.045	-0.074	-0.548*	-0.122
	[0.072]	[0.055]	[0.058]	[0.288]	[0.323]
Refugee Visa[2]	0.158**	0.054	-0.113	-0.999**	-0.213
	[0.078]	[0.054]	[0.073]	[0.397]	[0.318]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes
Observations	3449	4979	5003	5003	
Log Pseudolikelihood[3]	-2105.38	-2734.46	-2780.46	-4881.94	
Clusters	319	382	385	385	

Robust standard errors corrected for group effects within CMA/CA-country cells in brackets;
* significant at 10%; ** significant at 5%; *** significant at 1%;
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class
3 The word "pseudolikelihood" instead of likelihood is to stress the point that by specifying the -cluster- option we no longer have independent observations but rather independent clusters
NJ: Network Job, HJ: Have a Job, FJ: Formal Job

Table 9: Network influence in finding current/most recent job, at 2 year interview

	Probit Marginal Effects			Multinomial Logit	
	(1)	(2)	(3)	(4)	(5)
	NJ|HJ	NJ	HJ	FJ	NJ
Network Size	0.017	0.026	0.018*	0.244	0.315*
	[0.023]	[0.021]	[0.010]	[0.153]	[0.173]
Network Strength	0.116***	0.121***	0.017	0.006	0.574**
	[0.028]	[0.025]	[0.019]	[0.246]	[0.253]
Relative/Friend not close by	0.051	0.060	-0.001	-0.046	0.225
	[0.048]	[0.044]	[0.026]	[0.380]	[0.403]
Female	-0.023	-0.035*	-0.031***	-0.373**	-0.476***
	[0.020]	[0.019]	[0.011]	[0.169]	[0.172]
Age	0.000	-0.001	-0.002***	-0.031**	-0.031**
	[0.001]	[0.001]	[0.001]	[0.013]	[0.014]
Married	-0.029	-0.027	-0.006	0.010	-0.101
	[0.035]	[0.033]	[0.014]	[0.220]	[0.246]
Kids	0.033***	0.028***	-0.005	-0.144	0.002
	[0.011]	[0.010]	[0.006]	[0.097]	[0.089]
High school or less[1]	0.071	0.068	0.014	0.056	0.337
	[0.045]	[0.045]	[0.021]	[0.358]	[0.373]
University degree[1]	-0.095***	-0.107***	-0.034***	-0.366*	-0.772***
	[0.026]	[0.024]	[0.010]	[0.194]	[0.193]
Speak English well	-0.152***	-0.127***	0.017	0.516***	-0.115
	[0.023]	[0.022]	[0.011]	[0.166]	[0.171]
Speak French well	-0.049	-0.024	0.010	0.223	0.011
	[0.055]	[0.049]	[0.017]	[0.295]	[0.295]
Lived in Canada Before	0.020	0.012	0.008	0.190	0.237
	[0.055]	[0.049]	[0.023]	[0.393]	[0.407]
Principal Applicant	-0.014	-0.004	0.017	0.309	0.217
	[0.035]	[0.033]	[0.017]	[0.241]	[0.258]
Sponsored by family	0.068*	0.061*	-0.014	-0.340	-0.004
	[0.038]	[0.036]	[0.018]	[0.253]	[0.261]
Family Visa[2]	0.038	0.012	-0.033	-0.564	-0.416
	[0.062]	[0.059]	[0.031]	[0.354]	[0.390]
Refugee Visa[2]	0.200**	0.141*	-0.037	-1.010*	-0.076
	[0.095]	[0.082]	[0.046]	[0.544]	[0.533]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes
Observations	3183	3524	3322	3524	
Log Pseudolikelihood[3]	-1936.86	-2099.86	-904.40	-2845.99	
Clusters	298.00	312.00	250.00	312.00	

Robust standard errors corrected for group effects within CMA/CA-country cells in brackets;
* significant at 10%; ** significant at 5%; *** significant at 1%;
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class
3 The word "pseudolikelihood" instead of likelihood is to stress the point that by specifying the -cluster- option we no longer have independent observations but rather independent clusters
NJ: Network Job, HJ: Have a Job, FJ: Formal Job

Table 10: Network influence in finding current/most recent job, at 4 year interview

	Probit Marginal Effects			Multinomial Logit	
	(1)	(2)	(3)	(4)	(5)
	NJ|HJ	NJ	HJ	FJ	NJ
Network Size	0.020	0.023	0.008	0.309	0.392
	[0.023]	[0.022]	[0.008]	[0.305]	[0.320]
Network Strength	0.032	0.039	0.001	0.046	0.208
	[0.037]	[0.034]	[0.009]	[0.312]	[0.286]
Relative/Friend not close by	-0.027	-0.020	0.004	0.243	0.157
	[0.050]	[0.047]	[0.013]	[0.558]	[0.555]
Female	-0.042	-0.053*	-0.028***	-0.773**	-0.961***
	[0.028]	[0.027]	[0.009]	[0.321]	[0.356]
Age	-0.001	-0.001	-0.001**	-0.036*	-0.040**
	[0.001]	[0.001]	[0.000]	[0.020]	[0.020]
Married	-0.048	-0.031	0.020	0.713*	0.520
	[0.031]	[0.031]	[0.017]	[0.398]	[0.436]
Kids	0.043***	0.037***	-0.005	-0.263	-0.070
	[0.013]	[0.012]	[0.004]	[0.163]	[0.147]
High school or less[1]	0.105**	0.094*	-0.003	-0.274	0.150
	[0.049]	[0.052]	[0.015]	[0.481]	[0.568]
University degree[1]	-0.061**	-0.065**	-0.008	-0.249	-0.511
	[0.027]	[0.027]	[0.009]	[0.365]	[0.392]
Speak English well	-0.123***	-0.113***	-0.001	0.252	-0.266
	[0.028]	[0.026]	[0.007]	[0.281]	[0.263]
Speak French well	-0.023	-0.020	-0.008	-0.249	-0.331
	[0.065]	[0.062]	[0.016]	[0.444]	[0.473]
Lived in Canada Before	0.071	0.066	0.003	0.002	0.320
	[0.058]	[0.057]	[0.016]	[0.612]	[0.666]
Principal Applicant	-0.072***	-0.076***	-0.009	-0.194	-0.516
	[0.027]	[0.028]	[0.007]	[0.312]	[0.333]
Sponsored by family	0.158***	0.154***	-0.001	-0.322	0.389
	[0.057]	[0.053]	[0.019]	[0.772]	[0.716]
Family Visa[2]	-0.035	-0.038	-0.009	-0.346	-0.498
	[0.075]	[0.070]	[0.027]	[0.945]	[0.881]
Refugee Visa[2]	0.075	0.107	0.015	0.632	1.015
	[0.115]	[0.107]	[0.009]	[0.809]	[0.748]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes
Observations	2474	2585	2083	2585	
Log Pseudolikelihood[3]	-1501.89	-1557.18	-336.05	-1850.08	
Clusters	241.00	246.00	121.00	246.00	

Robust standard errors corrected for group effects within CMA/CA-country cells in brackets;
* significant at 10%; ** significant at 5%; *** significant at 1%;
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class
3 The word "pseudolikelihood" instead of likelihood is to stress the point that by specifying the -cluster- option we no longer have independent observations but rather independent clusters
NJ: Network Job, HJ: Have a Job, FJ: Formal Job

Table11: Unemployment Duration, Dependent variable: log(days till first job)

	Censored Normal Regression		
Censored at	Six months	Two Years	Four Years
	(1)	(2)	(3)
Network Size	-0.165***	-0.169***	-0.157***
	[0.047]	[0.049]	[0.048]
Network Strength	-0.059	-0.037	-0.028
	[0.061]	[0.063]	[0.062]
Relative/Friend not close by	0.068	0.071	0.058
	[0.090]	[0.094]	[0.093]
Female	0.245***	0.287***	0.303***
	[0.045]	[0.046]	[0.046]
Age	0.013***	0.010***	0.010***
	[0.003]	[0.003]	[0.003]
Married	0.100*	0.104*	0.079
	[0.058]	[0.060]	[0.059]
Kids	0.014	0.032	0.033
	[0.024]	[0.025]	[0.024]
Speak English well	0.089*	0.010	0.015
	[0.047]	[0.049]	[0.048]
Speak French well	-0.097	-0.104	-0.072
	[0.119]	[0.122]	[0.120]
Lived in Canada Before	-0.283***	-0.277***	-0.337***
	[0.099]	[0.103]	[0.102]
Sponsored by family	-0.086	0.058	0.054
	[0.100]	[0.102]	[0.100]
Principal Applicant	-0.011	-0.048	0.013
	[0.076]	[0.079]	[0.078]
Family Visa[1]	0.178	0.049	-0.038
	[0.126]	[0.130]	[0.128]
Refugee Visa[1]	0.470***	0.322*	0.105
	[0.179]	[0.183]	[0.181]
High school or less[2]	-0.238***	-0.241***	-0.220***
	[0.078]	[0.080]	[0.079]
University degree[2]	0.098*	0.117**	0.104*
	[0.057]	[0.058]	[0.057]
Occupation before dummies	Yes	Yes	Yes
CMA/CA dummies	Yes	Yes	Yes
Country of birth dummies	Yes	Yes	Yes
Month of landing dummies	Yes	Yes	Yes
Observations	4695	4185	4097
Log Likelihood	-6244.78	-6645.44	-6545.09

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted visa category is the Economic visa class
2 The omitted education category is Some University education but no degree

Table 12: Wage Regressions for first jobs within six months- Difference in Differences

	Dependent Variable: Log(weekly wage)					
	OLS	Quantile regressions				
		0.25	0.5	0.75	0.5	0.75
					includes unemployed[1]	
	(1)	(2)	(3)	(4)	(5)	(6)
Network Size	-0.036	-0.044	-0.020	-0.059	0.181	-0.046
	[0.029]	[0.058]	[0.038]	[0.041]	[0.205]	[0.050]
Network Strength	0.056	0.094*	0.047*	0.044	0.070	0.063
	[0.038]	[0.048]	[0.024]	[0.038]	[0.049]	[0.039]
Median wage in network	0.003	-0.009	-0.007*	-0.009	-0.004	-0.008
(000s per annum)	[0.007]	[0.007]	[0.004]	[0.006]	[0.007]	[0.006]
Relative/Friend not close by	0.075	0.024	0.028	0.114**	0.028	0.055
	[0.063]	[0.073]	[0.035]	[0.054]	[0.071]	[0.056]
Female	-0.214***	-0.246***	-0.117***	-0.164***	-0.231***	-0.182***
	[0.030]	[0.034]	[0.036]	[0.027]	[0.036]	[0.029]
Age	-0.003	-0.002	-0.002**	-0.004**	-0.010***	-0.007***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
Married	-0.017	-0.008	-0.028	-0.036	-0.020	-0.040
	[0.045]	[0.045]	[0.027]	[0.035]	[0.047]	[0.037]
Kids	-0.026**	-0.016	-0.001	-0.014	-0.008	-0.012
	[0.013]	[0.018]	[0.010]	[0.014]	[0.019]	[0.015]
High school or less[2]	0.143***	0.072	0.049*	0.080*	0.185***	0.100**
	[0.034]	[0.054]	[0.027]	[0.041]	[0.058]	[0.045]
University degree[2]	0.029	-0.014	-0.005	-0.007	0.009	-0.033
	[0.035]	[0.043]	[0.021]	[0.033]	[0.044]	[0.035]
Speak English well	0.068**	-0.035	0.040**	0.083***	-0.034	0.070**
	[0.034]	[0.037]	[0.018]	[0.028]	[0.037]	[0.029]
Speak French well	-0.162	-0.044	-0.179***	-0.106	0.010	-0.152**
	[0.098]	[0.090]	[0.046]	[0.070]	[0.090]	[0.070]
Lived in Canada Before	0.085	0.039	0.053	0.144**	0.096	0.131**
	[0.081]	[0.072]	[0.037]	[0.059]	[0.074]	[0.061]
Principal Applicant	0.055	0.060	-0.001	-0.025	0.131**	0.007
	[0.049]	[0.058]	[0.028]	[0.043]	[0.057]	[0.044]
Sponsored by family	0.070	0.045	-0.016	-0.075	-0.019	-0.045
	[0.055]	[0.079]	[0.039]	[0.058]	[0.078]	[0.056]
Family Visa[3]	-0.200***	-0.154	-0.018	0.009	-0.182*	-0.028
	[0.069]	[0.097]	[0.047]	[0.071]	[0.097]	[0.071]
Refugee Visa[3]	-0.251**	-0.181	-0.057	-0.122	-0.255**	-0.154
	[0.098]	[0.122]	[0.063]	[0.097]	[0.121]	[0.099]
Occupation before dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3207	3207	3207	3207	4659	4659

For OLS, robust standard errors corrected for group effects within CMA/CA-country cells in brackets
For OLS, R-squared is 0.15 and number of clusters is 268.
* significant at 10%; ** significant at 5%; *** significant at 1%
1. Very low wages were assigned to those who are unemployed and they were then included in the quantile regressions
2 The omitted education category is Some University education but no degree
3 The omitted visa category is the Economic visa class

Table 13: Wage Regressions for first jobs within two years- Difference in Differences
Dependent Variable: Log(weekly wage)

	OLS	Quantile regressions		
		0.25	0.5	0.75
	(1)	(2)	(3)	(4)
Network Size	-0.043	-0.024	-0.045	-0.059
	[0.028]	[0.057]	[0.035]	[0.042]
Network Strength	0.022	0.065*	0.033	0.046
	[0.036]	[0.036]	[0.029]	[0.036]
Median wage in network	0.001	-0.002	-0.006	-0.010**
	[0.006]	[0.005]	[0.004]	[0.005]
Relative/Friend not close by	0.034	-0.021	-0.020	0.096*
	[0.062]	[0.053]	[0.042]	[0.051]
Female	-0.203***	-0.241***	-0.137***	-0.151***
	[0.029]	[0.025]	[0.020]	[0.026]
Age	-0.003*	-0.002	-0.003**	-0.004**
	[0.002]	[0.002]	[0.001]	[0.002]
Married	0.008	0.036	-0.011	-0.018
	[0.038]	[0.034]	[0.027]	[0.034]
Kids	-0.029***	-0.032**	-0.011	-0.020
	[0.011]	[0.013]	[0.011]	[0.013]
High school or less[1]	0.129***	0.111***	0.044	0.064
	[0.033]	[0.040]	[0.032]	[0.040]
University degree[1]	0.054	0.026	0.020	0.036
	[0.038]	[0.031]	[0.025]	[0.032]
Speak English well	0.069**	-0.027	0.054**	0.099***
	[0.028]	[0.027]	[0.021]	[0.026]
Speak French well	-0.082	-0.009	-0.122**	-0.077
	[0.087]	[0.063]	[0.053]	[0.068]
Lived in Canada Before	0.082	0.056	0.082*	0.129**
	[0.080]	[0.054]	[0.044]	[0.058]
Principal Applicant	0.038	0.036	0.004	-0.032
	[0.048]	[0.042]	[0.033]	[0.041]
Sponsored by family	0.062	0.033	-0.042	-0.019
	[0.041]	[0.055]	[0.045]	[0.055]
Family Visa[2]	-0.177***	-0.140**	0.006	-0.025
	[0.062]	[0.069]	[0.055]	[0.067]
Refugee Visa[2]	-0.200**	-0.141*	-0.062	-0.105
	[0.085]	[0.084]	[0.072]	[0.088]
Occupation before dummies	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes
Observations	3816	3816	3816	3816

For OLS, robust standard errors corrected for group effects within CMA/CA-country cells in brackets
For OLS, R-squared is 0.14 and number of clusters is 294.
* significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class

Table 14: Wage Regressions for first jobs within four years- Difference in Differences
Dependent Variable: Log(weekly wage)

	OLS	Quantile regressions		
		0.25	0.5	0.75
	(1)	(2)	(3)	(4)
Network Size	-0.036	-0.028	-0.048	-0.061
	[0.028]	[0.059]	[0.035]	[0.041]
Network Strength	0.022	0.073**	0.039*	0.039
	[0.038]	[0.035]	[0.023]	[0.039]
Median wage in network	-0.001	-0.005	-0.006*	-0.013**
	[0.006]	[0.005]	[0.003]	[0.006]
Relative/Friend not close by	0.031	-0.023	-0.003	0.080
	[0.061]	[0.053]	[0.034]	[0.056]
Female	-0.210***	-0.239***	-0.142***	-0.159***
	[0.028]	[0.025]	[0.017]	[0.028]
Age	-0.003*	-0.001	-0.003***	-0.004**
	[0.002]	[0.002]	[0.001]	[0.002]
Married	0.016	0.030	-0.007	-0.025
	[0.038]	[0.034]	[0.022]	[0.037]
Kids	-0.031***	-0.029**	-0.010	-0.020
	[0.012]	[0.013]	[0.009]	[0.014]
High school or less[1]	0.121***	0.107***	0.030	0.050
	[0.034]	[0.041]	[0.027]	[0.043]
University degree[1]	0.064*	0.027	0.023	0.050
	[0.038]	[0.032]	[0.021]	[0.034]
Speak English well	0.065**	-0.014	0.052***	0.103***
	[0.025]	[0.027]	[0.017]	[0.028]
Speak French well	-0.055	-0.025	-0.068	-0.036
	[0.089]	[0.063]	[0.043]	[0.070]
Lived in Canada Before	0.041	0.021	0.031	0.084
	[0.079]	[0.054]	[0.036]	[0.061]
Principal Applicant	0.043	0.030	-0.003	-0.016
	[0.047]	[0.042]	[0.027]	[0.044]
Sponsored by family	0.075*	0.044	-0.008	-0.007
	[0.042]	[0.055]	[0.037]	[0.060]
Family Visa[2]	-0.214***	-0.153**	-0.020	-0.060
	[0.063]	[0.070]	[0.045]	[0.073]
Refugee Visa[2]	-0.220***	-0.134	-0.081	-0.167*
	[0.085]	[0.086]	[0.058]	[0.093]
Occupation before dummies	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes
Observations	3946	3946	3946	3946

For OLS, robust standard errors corrected for group effects within
CMA/CA-country cells in brackets
For OLS, R-squared is 0.14 and number of clusters is 298.
* significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class

Table 15: Wage Regressions augmented with interaction of method of job finding and network strength, for first jobs within six months-Dependent variable: Log(weekly wages)

	OLS	Quantile Regressions		
		0.25	0.5	0.75
	(1)	(2)	(3)	(4)
Network size	-0.036	-0.041	-0.021	-0.054
	[0.029]	[0.057]	[0.038]	[0.041]
Network Strength	0.068	0.128***	0.064**	0.052
	[0.045]	[0.049]	[0.031]	[0.044]
Network Job	-0.002	0.172**	0.023	-0.031
	[0.047]	[0.067]	[0.044]	[0.061]
Network Job*Network Strength	-0.032	-0.164**	-0.028	-0.026
	[0.053]	[0.072]	[0.047]	[0.065]
Median wage in network	0.003	-0.007	-0.006	-0.008
(000s per annum)	[0.007]	[0.006]	[0.004]	[0.006]
Relative/Friend not close by	0.074	0.019	0.051	0.109*
	[0.062]	[0.062]	[0.041]	[0.056]
Female	-0.215***	-0.239***	-0.152***	-0.163***
	[0.030]	[0.030]	[0.020]	[0.028]
Age	-0.003	-0.001	-0.003**	-0.004**
	[0.002]	[0.002]	[0.001]	[0.002]
Married	-0.018	-0.002	-0.028	-0.048
	[0.045]	[0.040]	[0.026]	[0.036]
Kids	-0.025*	-0.026*	-0.012	-0.007
	[0.013]	[0.016]	[0.010]	[0.014]
High school or less[1]	0.146***	0.058	0.051*	0.070*
	[0.033]	[0.046]	[0.031]	[0.042]
University degree[1]	0.027	-0.015	-0.003	-0.009
	[0.036]	[0.037]	[0.024]	[0.034]
Speak English well	0.065**	-0.039	0.041**	0.073**
	[0.033]	[0.032]	[0.021]	[0.028]
Speak French well	-0.166*	-0.067	-0.183***	-0.084
	[0.098]	[0.078]	[0.053]	[0.072]
Lived in Canada Before	0.084	0.040	0.059	0.140**
	[0.081]	[0.062]	[0.043]	[0.060]
Principal Applicant	0.055	0.066	-0.001	-0.037
	[0.049]	[0.050]	[0.032]	[0.043]
Sponsored by family	0.070	0.046	-0.049	-0.065
	[0.055]	[0.067]	[0.044]	[0.060]
Family Visa[2]	-0.196***	-0.168**	0.015	0.017
	[0.070]	[0.082]	[0.054]	[0.072]
Refugee Visa[2]	-0.245**	-0.186*	-0.030	-0.151
	[0.097]	[0.106]	[0.073]	[0.100]
Occupation before dummies	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes
Observations	3207	3207	3207	3207

For OLS, robust standard errors corrected for group effects within CMA/CA-country cells in brackets. For OLS, R-squared is 0.15 and number of clusters is 268.
* significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class

Table 16: Wage Regressions augmented with interaction of method of job finding and network strength, for first jobs within two years-Dependent variable: Log(weekly wages)

	OLS	Quantile Regressions		
		0.25	0.5	0.75
	(1)	(2)	(3)	(4)
Network Size	-0.042	-0.024	-0.044	-0.061
	[0.028]	[0.057]	[0.035]	[0.042]
Network Strength	0.032	0.101**	0.044	0.054
	[0.045]	[0.045]	[0.037]	[0.043]
Network Job	-0.043	0.133**	-0.013	-0.069
	[0.049]	[0.063]	[0.051]	[0.057]
Network Job*Network Strength	-0.014	-0.142**	-0.022	-0.029
	[0.059]	[0.067]	[0.055]	[0.062]
Median wage in network	0.000	-0.002	-0.006	-0.013**
(000s per annum)	[0.006]	[0.006]	[0.005]	[0.006]
Relative/Friend not close by	0.033	-0.020	-0.010	0.097*
	[0.062]	[0.059]	[0.047]	[0.053]
Female	-0.205***	-0.243***	-0.137***	-0.147***
	[0.029]	[0.028]	[0.023]	[0.027]
Age	-0.003*	-0.002	-0.003*	-0.004**
	[0.002]	[0.002]	[0.001]	[0.002]
Married	0.007	0.033	-0.003	-0.028
	[0.039]	[0.038]	[0.030]	[0.035]
Kids	-0.028**	-0.032**	-0.011	-0.015
	[0.011]	[0.015]	[0.012]	[0.014]
High school or less[1]	0.135***	0.103**	0.049	0.050
	[0.032]	[0.045]	[0.037]	[0.041]
University degree[1]	0.051	0.024	0.015	0.015
	[0.039]	[0.035]	[0.029]	[0.033]
Speak English well	0.064**	-0.036	0.043*	0.086***
	[0.028]	[0.030]	[0.024]	[0.027]
Speak French well	-0.087	-0.033	-0.125**	-0.081
	[0.087]	[0.070]	[0.060]	[0.071]
Lived in Canada Before	0.080	0.058	0.073	0.140**
	[0.081]	[0.058]	[0.050]	[0.060]
Principal Applicant	0.036	0.036	0.004	-0.021
	[0.048]	[0.048]	[0.038]	[0.043]
Sponsored by family	0.065	0.038	-0.041	-0.012
	[0.042]	[0.063]	[0.051]	[0.058]
Family Visa[2]	-0.173***	-0.140*	-0.007	-0.040
	[0.062]	[0.079]	[0.063]	[0.070]
Refugee Visa[2]	-0.191**	-0.131	-0.063	-0.157*
	[0.085]	[0.100]	[0.082]	[0.091]
Occupation before dummies	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes
Observations	3816	3816	3816	3816

For OLS, robust standard errors corrected for group effects within CMA/CA-country cells in brackets. For OLS, R-squared is 0.14 and number of clusters is 294.
* significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class

Table 17: Wage Regressions augmented with interaction of method of job finding and network strength, for first jobs within four years-Dependent variable: Log(weekly wages)

	OLS	Quantile Regressions		
Quantile Number		0.25	0.5	0.75
	(1)	(2)	(3)	(4)
Network Size	-0.036	-0.028	-0.049	-0.050
	[0.028]	[0.059]	[0.035]	[0.040]
Network Strength	0.031	0.117**	0.056*	0.055
	[0.047]	[0.048]	[0.030]	[0.045]
Network Job	-0.044	0.115*	-0.009	-0.074
	[0.050]	[0.065]	[0.042]	[0.061]
Network Job*Network Strength	-0.013	-0.129*	-0.030	-0.025
	[0.061]	[0.070]	[0.045]	[0.066]
Median wage in network	-0.001	-0.005	-0.006	-0.014**
(000s per annum)	[0.006]	[0.006]	[0.004]	[0.006]
Relative/Friend not close by	0.030	-0.018	0.005	0.096*
	[0.061]	[0.062]	[0.039]	[0.058]
Female	-0.212***	-0.235***	-0.150***	-0.159***
	[0.029]	[0.030]	[0.019]	[0.029]
Age	-0.003*	-0.001	-0.002**	-0.004**
	[0.002]	[0.002]	[0.001]	[0.002]
Married	0.014	0.036	-0.003	-0.015
	[0.039]	[0.040]	[0.025]	[0.038]
Kids	-0.030***	-0.034**	-0.012	-0.019
	[0.012]	[0.015]	[0.010]	[0.015]
High school or less[1]	0.127***	0.103**	0.031	0.060
	[0.032]	[0.047]	[0.031]	[0.045]
University degree[1]	0.061	0.031	0.025	0.040
	[0.038]	[0.037]	[0.024]	[0.035]
Speak English well	0.060**	-0.030	0.039*	0.099***
	[0.025]	[0.032]	[0.020]	[0.029]
Speak French well	-0.057	-0.027	-0.075	-0.061
	[0.089]	[0.073]	[0.049]	[0.072]
Lived in Canada Before	0.040	0.024	0.048	0.110*
	[0.079]	[0.062]	[0.041]	[0.063]
Principal Applicant	0.041	0.027	0.004	-0.024
	[0.047]	[0.050]	[0.031]	[0.046]
Sponsored by family	0.078*	0.049	-0.007	-0.008
	[0.043]	[0.063]	[0.042]	[0.063]
Family Visa[2]	-0.210***	-0.153*	-0.039	-0.043
	[0.063]	[0.080]	[0.052]	[0.076]
Refugee Visa[2]	-0.211**	-0.126	-0.107	-0.151
	[0.084]	[0.099]	[0.066]	[0.095]
Occupation before dummies	Yes	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes	Yes
Observations	3946	3946	3946	3946

For OLS, robust standard errors corrected for group effects within CMA/CA-country cells in brackets. For OLS, R-squared is 0.14 and number of clusters is 298.
* significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted education category is Some University education but no degree
2 The omitted visa category is the Economic visa class

Table 18: Skill Change between First Job in Canada and Job before Migration
Highest Skill Immigrants only
Dependent variable: 1=No Change 0=Decrease in Skill Level

	Probit, Marginal Effects		
For jobs within	Six months	Two Years	Four Years
	(1)	(2)	(3)
Network Size	-0.024	-0.041	-0.041
	[0.034]	[0.027]	[0.026]
Network Strength	-0.004	0.007	0.014
	[0.050]	[0.051]	[0.051]
Median wage in network	0.014*	0.018***	0.018***
(000s per annum)	[0.007]	[0.007]	[0.007]
Relative/Friend not close by	-0.008	-0.015	-0.009
	[0.063]	[0.064]	[0.067]
Female	0.029	0.060*	0.067**
	[0.031]	[0.033]	[0.033]
Age	-0.007***	-0.006***	-0.006***
	[0.002]	[0.002]	[0.002]
Married	-0.015	-0.005	-0.001
	[0.032]	[0.027]	[0.029]
Kids	-0.034**	-0.041***	-0.039***
	[0.016]	[0.014]	[0.014]
Speak English well	0.098***	0.102***	0.112***
	[0.031]	[0.028]	[0.027]
Speak French well	-0.056	-0.021	-0.024
	[0.057]	[0.066]	[0.068]
Lived in Canada Before	0.399***	0.353***	0.350***
	[0.080]	[0.079]	[0.080]
Sponsored by family	0.115	0.133	0.132
	[0.163]	[0.108]	[0.108]
Principal Applicant	0.137**	0.097**	0.102**
	[0.056]	[0.047]	[0.047]
Family Visa[1]	-0.190***	-0.197**	-0.202**
	[0.060]	[0.081]	[0.080]
University degree[2]	0.050	0.042	0.048
	[0.090]	[0.076]	[0.075]
Occupation before dummies	Yes	Yes	Yes
Country of Birth dummies	Yes	Yes	Yes
CMA dummies	Yes	Yes	Yes
Observations	1054	1303	1337
Log Pseudolikelihood	-502.37	-671.84	-694.34
Clusters	112.00	127.00	127.00

Robust standard errors corrected for group effects within CMA/CA-country groups in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted visa category is the Economic visa class
2 The omitted education category is Some University education but no degree

Table 19: Skill Change between First Job in Canada and Job before Migration
Highest Skill Immigrants only
Dependent variable: 1=No Change 0=Decrease in Skill Level

	Probit, Marginal Effects		
For jobs within	Six months	Two Years	Four Years
	(1)	(2)	(3)
Network Size	-0.016	-0.036	-0.038
	[0.034]	[0.027]	[0.027]
Network Strength	0.014	0.020	0.021
	[0.052]	[0.052]	[0.052]
Network Job	-0.126***	-0.147***	-0.156***
	[0.047]	[0.048]	[0.046]
Network Job*Network Strength	-0.021	0.008	0.032
	[0.055]	[0.053]	[0.054]
Median wage in network	0.014*	0.018**	0.019***
(000s per annum)	[0.007]	[0.007]	[0.007]
Relative/Friend not close by	-0.014	-0.014	-0.008
	[0.063]	[0.065]	[0.068]
Female	0.018	0.052	0.061*
	[0.030]	[0.034]	[0.034]
Age	-0.006***	-0.006***	-0.006***
	[0.002]	[0.002]	[0.002]
Married	-0.012	0.001	0.005
	[0.030]	[0.027]	[0.028]
Kids	-0.031*	-0.040***	-0.039**
	[0.017]	[0.015]	[0.015]
Speak English well	0.087***	0.095***	0.106***
	[0.029]	[0.028]	[0.027]
Speak French well	-0.066	-0.025	-0.028
	[0.057]	[0.069]	[0.070]
Lived in Canada Before	0.403***	0.349***	0.347***
	[0.084]	[0.085]	[0.086]
Sponsored by family	0.119	0.155	0.151
	[0.166]	[0.111]	[0.109]
Principal Applicant	0.117**	0.078*	0.087*
	[0.058]	[0.046]	[0.046]
Family Visa[1]	-0.183***	-0.202***	-0.206***
	[0.063]	[0.074]	[0.075]
University degree[2]	0.052	0.033	0.041
	[0.087]	[0.078]	[0.076]
Observations	1054	1303	1337
Log Pseudolikelihood	-490.53	-658.11	-681.90
Clusters	112.00	127.00	127.00

Robust standard errors corrected for group effects within CMA/CA-country groups in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%
1 The omitted visa category is the Economic visa class
2 The omitted education category is Some University education but no degree