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Matloob Piracha
Massimiliano Tani
Matias Vaira-Lucero

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Matloob Piracha
University of Kent
and IZA

Massimiliano Tani
Macquarie University
and IZA

Matias Vaira-Lucero
Macquarie University

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Social Capital and Immigrants' Labour Market Performance[1]

This paper analyses the role of social capital on immigrants' labour market outcomes. We use the "principal component analysis" (PCA) to build an index of social networks and explore its impact on the probability of getting a job and on wage levels using the Households Income and Labour Dynamics in Australia (HILDA) longitudinal survey data. We find a positive effect of social capital on migrants' employment outcomes and wages, especially for women. Distinguishing employment into blue and white-collar jobs, we find that social capital only affects the probability of getting a white-collar job. These results suggest that promoting opportunities to create social capital has a beneficial effect on migrants' integration in the host country.

JEL Classification: F22, J01, J61, Z13

Keywords: immigrants, labour market, social capital, HILDA survey, Australia

Corresponding author:

Matloob Piracha
School of Economics
Keynes College
University of Kent
Canterbury, Kent CT2 7NP
United Kingdom
Email: M.E.Piracha@kent.ac.uk

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1. INTRODUCTION

Those seeking employment use a number of ways to find a job, including visiting relevant websites, applying through employment agencies and, in some cases, approaching the employer directly without any referral. However, a prevalent way of seeking employment seems to be the use of personal networks, with 25 to 80 percent of jobs obtained through this process (Ioannides & Loury, 2004). This finding provides support to the argument that social capital, much like human capital, plays a crucial role in the labour market as it helps individuals to obtain employment and, possibly, get better wages (Lin, 1999). Although the hypothesis that social networks significantly affect the functioning of the labour market is plausible in principle, there is only limited empirical economic literature studying their impact on an individual's labour market outcome.[2] Even less research exists on whether, if at all, social capital matters for an immigrant's access to employment in the host country. This paper attempts to fill this gap using evidence from a longitudinal survey of Australian households.

Immigration to Australia is characterised by a large contingent of migrants originating from countries that are economically less developed than Australia, and/or have a language and cultural background other than English. Being raised and educated in a distinct *milieu* than that of the country of destination may compromise a migrant's skills and qualifications transferability once migration occurs: the migrant may not be able to offer skills and knowledge that an Australian employer expects or takes for granted. This could leave the migrant in a disadvantaged position relative to a native-born because the employer may believe that hiring the migrant comes with an additional unnecessary risk and possible future costs for re-training or job underperformance (Chiswick, 1978). In light of those arguments, social capital could ease the path of migrants into the social and economic life in the host country by providing opportunities to getting to know them, perhaps in informal circumstances, where it is possible to observe their character, attitudes and skills, understand their motivations, and familiarise with their history. At the same time social capital may offer new migrants insights and tips on the way of life of their new country of residence. Social capital's possible role in facilitating the socio-economic assimilation of migrants may also lead to an improved access or faster progress into the host country's labour market.

[2] Even though an economist was the first one to study the role of social networks (Loury, 1977), most of the research on the topic has been carried out by sociologists.

Even though the concept of social capital has been used in various ways to analyse different contexts such as educational attainment (Sun, 1999), child wellbeing (Coleman, 1988) and health service utilization (Deri, 2005), much less attention has been devoted to its effect on labour market outcomes. This is perhaps because of the difficulties in trying to find accurate measures of social capital. It is in fact difficult to identify exactly what social capital is. As a result, its definition consists of a set of characteristics (activities and attitudes, mostly), some of which are measured in detailed individual survey data.

From a general economic viewpoint, the literature points out that social capital is linked to economic success, hence implying that cooperation through personal networks is a profitable activity since it enables individuals to provide each other with valuable and otherwise restricted information and services (Herreros, 2004). Moreover, as all forms of capital generating a potential flow of benefits over a future time horizon, social capital can be considered as an asset that migrants acquire over time with the prospect of reciprocation at some stage in the future.

Besides the challenge to formulate an exact definition, the study of social capital is affected by the type of available data. Previous studies tend to rely on cross-sectional data (Derrick, 2011; Lancee, 2010; Stone, Gray, & Hughes, 2003). These unfortunately limit the scope of the studies, as they are not suited to identify the causal direction of the possible relationship between social capital and labour market outcomes.[3] Without longitudinal data it is difficult to tell if immigrants have fewer or worse employment possibilities than natives because they have fewer personal contacts or if immigrants have more limited personal networks because they are more often unemployed and underemployed.

To evaluate the labour market effect of migrants' personal networks and social contacts we exploit information unique to the Household Income and Labour Dynamics in Australia (HILDA), a detailed longitudinal survey data. Using panel data estimation techniques and the using of principal component analysis to construct a social capital index based on a set of relevant questions asked in the HILDA, we find that social capital has a positive effect on immigrants' probability of employment, especially in the case of white-collar occupations and for women. And for some cases we find positive effects of social capital on wages as well.

[3] One exception is Xue (2008) who uses Canadian survey data and find a causal relation between social capital and employment outcomes of migrants.. However, the data has only three waves over a period of two years and it has information on immigrants only, which limits the scope of their analysis.

The rest of the paper is organised as follows: Section 2 summarises the literature on social capital. Section 3 presents the data. Section 4 discusses the empirical methodology. Section 5 presents the results. Section 6 concludes.

2. SOCIAL CAPITAL, EMPLOYMENT and WAGES

There are several definitions of social capital and they seem to differ by field of study. 'Social capital' generally refers to an individual's network of social relations. These are characterized by norms of trust and reciprocity, and lead to outcomes of mutual benefit (Bourdieu, 1993; Coleman, 1988; Putnam, Leonardi, & Nanetti, 1993). The United Kingdom's Office for National Statistics (Brook, 2005) proposes three forms of social capital, which identify interactions in three different spheres of a person's range of social relations: namely "bonding", "bridging" and "linking". "Bonding" refers to interactions with closely associated people such as family or good friends. "Bridging" includes the contacts with casual friends, colleagues or associates. This form of social connectivity has been identified as positively contributing to the diffusion of information and trust among economic agents, with a possible increase in the volume of transactions and, ultimately, economic growth (Sabatini, 2009). "Linking" covers interactions with organizations through the membership of social, educational, political or voluntary institutions. These interactions may help an individual to extend networks and further expand his/her social capital.

The literature supports that social contacts facilitate economic opportunities, transactions and economic growth because they allow people to leverage on resources such as knowledge, information and influence held by others (Ioannides & Loury, 2004; Lin, 1999; Mouw, 2003). Immigrants appear to benefit from their social contacts by obtaining useful public and restricted information about the labour market as well as regulations and practice to start-up new businesses, which are specific to the host country (Aguilera & Massey, 2003).

Among the group of activities pointed out by the literature as related to different dimensions of social capital, some are linked to activities carried out during leisure time or centred on social participation, such as volunteer work, active involvement in community-based associations or frequent social contacts with friends, family or neighbours (Brook, 2005). All these activities could potentially enrich migrants' networks of local contacts.

The economic foundations of social capital theory are based around the potential economic benefit, for an individual, of having access to a network of people through social interactions. A social network can keep track of opportunities in the labour market and act as a matching function in which finding a job for one of the members depends on the group's sharing of information about current or future jobs' availability obtained by word-of-mouth or other informal channel (Calvo-Armengol & Zenou, 2005). Workers who are better connected thanks to a larger or a higher 'quality' (e.g. with individuals holding prestigious or powerful jobs) social network are more likely to fare better than those who have a very limited network.

Immigrants are likely to be less connected than natives in the host country and therefore have lower chances of getting employment through social networks especially early after arrival. Though migrants may have a smaller social network than natives in their country of destination (also because, for a given age, they may have lived fewer years there than a native), they may nevertheless have developed social ties to other immigrant groups, or those who had migrated previously, with more focus and attention than if they did not migrate. This then could imply that migrants may not necessarily be significantly less connected than natives. Possibly, migrants could have a large number of 'weak-ties' which Montgomery (1991) shows as being very important in determining an individual's labour market outcome.[4]

In terms of wage determination, there is some evidence of a positive relationship between social network and wage levels (Labini, 2004; Rosenbaum, DeLuca, Miller, & Roy, 1999). As members of a social group are likely to be similar in observed, and perhaps, unobserved characteristics, it could be argued that the employees recommend, when a vacancy opens up, people who are very similar to them. This is also likely to happen because an existing employee's reputation with his/her employer is at stake as well. The theory then predicts that a difference in social structure could result in wage differentials among those with higher density of social ties (e.g., natives) compared to others (e.g. immigrants). Calvó-Armengol and Jackson (2004) show that the wages of any socially-connected agent are positively correlated across the social network. There is indeed also a possibility that there exists negative correlation between employment status, wages and network size, which results from competition for information about certain jobs. Calvó-Armengol and Jackson (2004) show that the negative relationship will only exist in the short-run as in the long-run benefits of

[4] Granovetter (1973) argued that workers are more likely to have obtained jobs through "weak-ties" (acquaintances) rather than "strong-ties" (family and friends).

improved wage status of networks outweigh the short run competition effects. Overall therefore, wages should increase with network diversity and quality.

As the HILDA database includes both natives and immigrants and contains questions on the social activity and connectedness of the surveyed, we can estimate the effect of social networks on labour market outcomes. As network effects may differ across gender and job types, we carry out separate analyses for males and females and on white and blue-collar jobs. Consistent with other research (Hu, Kaplan, & Dalal, 2010; Pearson, 1998; Toppinen-Tanner, Kalimo, & Mutanen, 2002), we classify occupations such as managers and administrators and, advanced clerical and service workers as white-collar jobs, and skilled trades, craft workers, machine operators, drivers, labourers, agricultural workers and other manual workers as blue-collar jobs .

3. DATA AND DESCRIPTIVE STATISTICS

The Household Income and Labour Dynamics in Australia (HILDA) is a longitudinal annual survey that collects information about the economic and subjective well-being, labour market dynamics and family dynamics of approximately 13,000 individuals from about 7000 households. It began in 2001.[5]

The advantage of HILDA's panel structure is that it reduces the possibility of heterogeneity bias in the estimations, as one can control for individual time invariant and time varying characteristics. Though HILDA suffers from attrition, as individuals drop out of the survey (e.g. if they emigrate from Australia), and attrition appears to be non-random, the dataset has been adjusted for attrition through the careful use of sample weights to minimise the possibility of bias (Summerfield et al., 2012).

The sample used for the empirical analysis is restricted to persons between 25 and 59 years of age. This restriction reduces the possibility of including those who may be full time students or considering retirement. We also exclude those not in the labour force or self-employed, those who refuse to give information about their country of origin, and those who report positive working hours but zero or not-reported hourly wages.

[5] See Summerfield et al. (2012) for more details

We performed the analysis on an unbalanced panel for two subsamples: one includes all migrants and native-born Australians. It contains 47,031 observations. The second sub-sample contains only migrants[6] and has 10,196 observations. Table 1 in displays the number of observations, by wave, for the whole panel.

Dependent and Independent variables

The dependent variables for this study are employment status and individual hourly wages. For employment status, we create a dummy variable, which equals 1 if the person is employed and zero otherwise. The hourly wage is calculated as the gross weekly salary from all jobs divided by the total number of hours worked in that week.

To compute the effect of social capital on the labour market outcomes of migrants, various indicators have been proposed in the literature. These relate to different dimensions of life such as social participation, civic participation, social networks and social support, reciprocity and trust as well as subjective views about the locale where one lives (Brook, 2005). To capture this multidimensionality of the concept and avoid including several and possibly correlated indicators in the estimation, we opted for constructing a social capital index using principal component analysis (PCA). Principal component analysis (PCA) is a multivariate statistical technique used to reduce the number of variables in a data set into a smaller number of dimensions. For an initial set of "n" correlated variables, it creates uncorrelated indices, where each is obtained as a weighted combination of the initial variables. The index we constructed to proxy for the social capital for each individual is a weighted combination of several variables highlighted by the UK's Office for National Statistics as attributes of social capital (Brook, 2005). Detailed explanations on its construction and calculation are provided in Appendix A.

The variables capturing different dimensions of social capital and covered in the HILDA include:

(1) Social participation, as answered to the question on *Active membership to sporting/hobby/community based club or association*. We construct a dummy variable equals to one if the answer is yes and zero otherwise.

(2) Social networks and social support, as answered in questions about:

(i) *Frequency of contacts:* respondents were asked in the Self Completion Questionnaire (SCQ) about the frequency of social contact with neighbours, friends

[6] Estimation results from the migrants' sample available from the authors upon request.

or family not living with them. The possible answers were categories going from 1 to 7, where 1 was "less often than once every three months" and 7 was "every day". We rescaled this variable by creating a dummy equal to one for responses above the average response and zero otherwise. We implement this recoding of categorical variables in order to simplify the process of constructing the index using PCA methodology.

(ii) Exchange of help: this question asks respondents to quantify how much support they can get from other people. It is a categorical variable (from 1 to 7) asking the respondent to rank agreement with the following statement: "I seem to have a lot of friends". A dummy variable was created equalling 1 if the response was above the average and zero otherwise.

(iii) Control and satisfaction with life: a set of questions in HILDA asks about satisfaction with different aspects of life. We chose a question on how the respondents feel about their participation/integration in their local communities. It is a categorical variable that goes from zero (totally dissatisfied) to 5 (neutral) and then 6 to a final 10 if the person is totally satisfied. We also rescale this variable by creating a dummy variable equal to 1 for cases above "neutral" and zero otherwise.

(3) Reciprocity and trust, as asked in the HILDA question on *Help from others*: the response is coded as a categorical variable ranging from 1 (strongly disagree) to 7 (strongly agree) asking respondents how much they approve the following statement: "I often need help from other people but cannot get it".

Other questions looking at aspects of social capital such as civil participation, views of the local area and number and diversity of the networks were not asked consistently in every year of the survey. Therefore these answers cannot be used in the analysis. In contrast, the estimations include some indicators of human capital such as education level, language skills and work experience.

When more than one variable proxying for social capital was used, we performed Wald tests for the statistical significance of their linear combination to check that our estimations using the index were robust.

Table 2 presents the demographic and socioeconomic characteristics together with the variables related to social capital for native-born Australians and migrants, both also subdivided by gender. On average, male and female immigrants earn more than native-born Australians. One possible explanation is that immigrants seems to have higher levels of human capital (see Table 2) because they are better educated and have more work experience than native-born Australians. Australia's immigration policy favours the settlement of highly educated foreign citizens.

Most of the female immigrants work in white-collar occupations in the services industry, which is also the case for the native born, both males and females. There are also important differences in terms of age and marital status. On average, migrants seems to be older than their local Australian counterparts (43 vs. 40 years old) and a larger percentage of migrants are married or in a de-facto relationship than natives. This is especially the case for men (79% vs. 75%). In terms of places or residence, migrants tend to be concentrated in large cities (80% in the case of men) or inner-regional areas (15%). Native-born Australians are more dispersed across the country with only 62% living in cities and a large 26% living in inner regional areas. A very small proportion of migrants live in remote or very remote areas of Australia.

Regarding the means of variables used as indicators of social capital, there are important differences between men and women regarding their average indicators of social capital. Women seem to socialize more often with friends or relatives outside their close circle than men. A larger proportion of women also perform hours of volunteer work and feel more satisfied with the degree of community participation vis-à-vis their male counterparts. There is also a marked difference between native-born Australians and migrants in terms of active membership to clubs and community-based associations, where Australian men are more likely to participate in these activities vis-a-vis immigrant men.

4. EMPIRICAL METHODOLOGY

We apply a logit regression to estimate the probability of getting employment. The likelihood of getting employment can be presented as an unobserved latent variable y* where:

$$y_{it}^{*} = x_{it}^{'}\beta + \mu_i + \varepsilon_{it} \qquad i = 1,\dots n \quad \text{and} \quad t = 1,\dots,T \;;$$

$$y_{it} = 1 \;\; \text{If} \quad y_{it}^{*} > 0$$

$$y_{it} = 0 \;\; \text{Otherwise}$$

where *i* indexes individuals and *t* represents time periods.

The total number of periods is nine (T_i=9), corresponding to years 2002 to 2010. We do not observe y_{it}^* but rather whether an individual is employed ($y_{it} = 1$) or not ($y_{it} = 0$). There are z independent variables in the vector X_{it}. All of them are observable: some vary with time while others are time-invariant.

Given the longitudinal feature of HILDA, we apply panel data estimation techniques to take unobserved individual specific effect, (μ_i), into account. By so doing, we reduce the effect of heterogeneity across individuals and limit the estimation bias arising from omitted variables. Since HILDA has a large number of cross-sectional units but a few periods, we focus on heterogeneity across units rather than time series autocorrelations.

Within the econometric models available for panel data when the dependent variable is discrete (binary-choice), the two main options are probit (normal distribution) or logit (logistic distribution) models using fixed effect or a random effect methodology. Fixed effect logit model relies on the assumption that the unobserved individual effects (μ_i) are correlated with X_{it}. Fitting this model using the full maximum-likelihood approach leads to incidental parameters problem since μ_i and β are unknown parameters, and as N $\rightarrow \infty$ for a fixed T, the number of parameters μ_i increases with N and μ_i cannot be consistently estimated for a fixed T (Baltagi, 2009). The usual solution around this was proposed by Chamberlain (1980), who finds that $\sum_{t=1}^{T} y_{it}$ is a minimum sufficient statistic for μ_i. This solution suggests maximizing the following conditional likelihood function:

$$L_c = \prod_{i=1}^{N} \Pr\left(y_{i1},\ldots,y_{iT} / \sum_{t=1}^{T} y_{it} \right).$$

The limitation with this approach is that it may potentially significantly reduce the sample size since only individuals who switch status (from 1 to zero or zero to 1) are included in the estimation. The other terms, corresponding to individuals who do not switch status, add nothing to the conditional log likelihood (log 1 =0), and are therefore discarded. Furthermore, by using this model we cannot estimate coefficients for time-invariant variables, which are of interest for our study, such as individuals' countries of birth. To overcome these limitations we can use the random effect logit approach, which does not imply a reduction in the size of the sample and also allows one to estimate coefficients for time-invariant variables.

There is also the option of performing a pooled-logit estimation. However in that case we will not be exploiting the advantage of having a panel dataset and hence will remain exposed to the possibility of bias due to omitted variables. Therefore, we estimate the probability of employment using a random effect logit method.

We use a panel data model starting with fixed effect (FE) and random effect (RE) estimations to measure the effects of social capital on hourly wages as an additional indicator of labour market outcome. After performing a Hausman test suggesting to reject the null hypothesis of a consistent RE estimation, we choose to use the instrumental variable estimator proposed by Hausman and Taylor (1981) which, unlike the FE version, also allows one to estimate time-invariant variables (like the country of birth). The Hausman and Taylor (HT) estimator fits panel-data random-effects models when some of the covariates are correlated with the unobserved individual-level random effect (μ_i) but none of the explanatory variables (X_{it}) are correlated with the idiosyncratic error (ε_{it}). Since it is an instrumental variable estimator, it presents the additional advantage that the instruments are derived within the model rather than externally.[7]

The decision about which variables are to be considered endogenous and which ones are going to be included in the model is crucial in order to get the right instruments and hence an unbiased and consistent HT estimator. We include experience and the square of experience as variables possibly correlated with unobserved individual random effects. It is intuitively clear that experience would be correlated with the unobserved effects since the literature often assume ability and motivation as unobserved characteristics affecting individuals' behaviour. It is not unreasonable to expect that these variables are different between natives and immigrants.

To check for the existence of weak instrument, we perform individual regressions for each of the endogenous variables included on the time-varying exogenous variables paying particular attention to the F-stats of the regressions (Staiger & Stock, 1997). The results support that the instruments used for the endogenous variables are satisfactory to carry out the HT estimation.[8]

[7] See Cameron *et al* (2010) for a detailed explanation of transformations made to the model to obtain the instruments for the Hausman-Taylor estimator.

[8] Results from those tests are available from the author upon request

5. ESTIMATION RESULTS

The estimates on the probability of employment are presented in Table 3. Though reported, we included estimates from the pooled probit model only for purposes of comparison, as the random effect logit model is the preferred benchmark given that it enables one to take advantage of the longitudinal characteristics of HILDA. Table 3 also shows the differences in the social capital effect by gender and Table 5 by type of occupation.

Social capital emerges as a highly relevant determinant of the probability of employment, especially for female migrants. Even though social capital is one of the factors which contribute positively to the probability of getting employment, the estimations also show that the effect is not equally significant for migrants from English speaking countries (ESC) or non-English speaking countries (NESC) compared to natives. For instance, per each unit of increase in the social capital index the odds of getting employment increase by 32% for all individuals, 28% in the case of ESC migrants and 17% for NESC migrants. Significant differences in the effect of social capital emerge in cases of individuals (natives or migrants) when occupations are distinguished in white- and blue-collar jobs. Per each unit of increase in the index of social capital, there is an 11.1% increase in the odds of employment in white-collar jobs but no significant effect in case of the blue collar sector. The different effect of social capital on getting a white- or blue-collar job is present regardless of gender.

Table 4 shows the estimation results obtained from the panel-data random effect logit model across all individuals as well as for men and women separately. The marginal effects for the variables capturing individual characteristics are in line with the explanations and findings of other empirical studies. Married individuals (male or female) are more likely to get employment than those who are single, divorced or widowed. There is also a significant negative effect on the probability of employment as individuals get older, which is larger in the case of men. Having young children (14 or younger) has also a negative effect on the probability of employment of both migrants and natives, not surprisingly showing a larger impact on women vis-à-vis their male counterparts.

To test the magnitude of the differences in the effects of social capital on ESC and NESC migrants compared to native-born Australians, we perform a Wald Test (see Table 4 in the appendix) of the joint significance for a linear combination of the two variables. The null hypothesis is that the sum of both coefficients (the index of social capital and the social capital for ESC or NESC) equals zero. The linearly combined coefficients are significant and positive only for migrant women regardless of whether from ESC or NESC background. They are instead statistically insignificantly different from zero for the subsample of men. This result is perhaps a symptom that migrant women may be at a disadvantage in the labour market and hence leverage on their social networks to increase their employment opportunities.

The results support that social capital clearly matters for individuals in terms of labour market outcomes though important differences arise when the analysis takes into account the gender and countries of origin of migrants. Social networks seem particularly important to get employment in white-collar occupations while they appear to be totally irrelevant to get a blue-collar job (see Table 5). With reference to the country of birth, we find no statistically significant differences for ESC or NESC vis-à-vis their native counterparts. As a robustness check we also analyse if there are differences by industry but the results obtained are similar to the analysis by occupations.[9]

Tables 6 and 7 present the results obtained from the fixed effect, random effect and Hausman-Taylor models using the logarithm of the hourly wage as a dependent variable. According to the Hausman-Taylor estimates, immigrant men and women earn significantly less compared to native-born Australians with similar characteristics, regardless of their country of origin being non-English (NESC) or English speaking (ESC). The returns to human capital are in line with previous studies and indicate a clear negative effect of education on wages if individuals have not finished high school, for both men and women. Positive effects arise when the highest level of education achieved is a bachelor's degree or higher.

The results suggest that social capital is highly relevant as a determinant of the hourly wage, contributing to increases in earnings for both migrants and natives. Further inspection, however, reveals that positive returns to social capital are statistically significantly different from zero only for women, while no such effect arises for the subsample of men. We interpret this result as the possible effect that women may be over-represented in casual or non-career oriented part-time jobs. These often paid low wage rates and provide fewer opportunities for training, development and career progression. Hence developing social capital may be a way to access those opportunities to progress in the labour market through a better job vis-à-vis a higher hourly wage.

[9] Results are available from the authors upon request.

6. CONCLUSIONS

Many studies have attempted to explain what social capital is and what type of indicators can be used to identify and measure it. Despite the complexity of these the limited existing literature on the topic has suggested that social capital matters for economic outcomes.

The directions and significance of the relationships between the social capital index, the probability of employment and the earnings of migrants are mixed. Our estimates show that the coefficient for the index of social capital is very much significant for all individuals (natives and migrants), but it is especially important for women and to access white-collar jobs. Wages are also positively affected by the existence of social networks but only in the case of women. Social capital has no effect on the hourly wages of men, regardless of where they were born.

Our findings show that social capital or personal networks are highly relevant to improve the labour market outcomes and integration of everyone in the society (not just immigrants). Even though we recognize the importance of social capital, we are also aware that designing legislation to improve the opportunities of migrants for the developing of networks is challenging. Since sometime personal networks are specifically built by migrants to improve access to employment information, social connections acquired through leisure-related activities (i.e. community participation, social gatherings, volunteer work) can be of great help in achieving good labour market outcomes. Policy makers should therefore recognize that funding to support organizations such as community centres, sports and cultural clubs or any communal or volunteer activity may indirectly contribute to improve the labour market integration of immigrants. Germany could be an example to follow, where policy makers implemented measures to improve personal networks within low-income communities where many immigrants reside. Those programs aim to get local residents involved in neighbourhood improvement activities such as parks clean-ups or even the coordination of social events (Drever & Hoffmeister, 2008).

Table 1: Size of the sample for each wave of the panel

		WAVE								
		2	3	4	5	6	7	8	9	10
Men	Immigrant	699	649	609	620	613	568	540	569	578
	Native-Born	2,184	2,089	2,030	2,078	2,129	2,115	2,143	2,237	2,241
	Total	2,883	2,738	2,639	2,698	2,742	2,683	2,683	2,806	2,819
Women	Immigrant	638	597	584	584	597	586	567	562	560
	Native-Born	2,098	2,014	1,977	2,079	2,151	2,157	2,177	2,182	2,263
	Total	2,736	2,611	2,561	2,663	2,748	2,743	2,744	2,744	2,823
TOTALS	total migrants	1337	1246	1193	1204	1210	1154	1107	1131	1138
	total natives	4,282	4,103	4,007	4,157	4,280	4,272	4,320	4,419	4,504
	total sample	5,619	5,349	5,200	5,361	5,490	5,426	5,427	5,550	5,642
	% migr/total	23.79%	23.29%	22.94%	22.46%	22.04%	21.27%	20.40%	20.38%	20.17%

Table 2: Descriptive Statistics (mean values) corresponding to wave 5 of the panel

		MEN		WOMEN	
Variable	Description	Natives	Migrants	Natives	Migrants
hgage	Age in years	40.14	42.64	40.79	43.11
dkids	Dummy=1 if household with children younger than 14	0.43	0.41	0.43	0.41
married	Marital Status (married or defacto =1)	0.74	0.78	0.71	0.75
hrwage	Hourly wage	25.90	26.52	22.04	23.20
exp	Experience	21.72	22.93	18.75	20.65
migesc	Dummy=1 if migrants is from an English speaking country	N/A	0.51	N/A	0.46
mignesc	Dummy=1 if migrants is from a non-English speaking country	N/A	0.49	N/A	0.54
ysm	Years since migration	N/A	23.05	N/A	24.48
englabil4	English Ability (Dummy=1 if speaks very well or native level)	1.00	0.21	1.00	0.24
nohsh	Dummy =1 if highest education is less than year 12	0.20	0.16	0.27	0.18
hschool	Dummy=1 if has high school completed	0.11	0.13	0.13	0.17
certificate	Dummy =1 if has a certificate or diploma	0.43	0.35	0.28	0.27
bachelor	Dummy=1 if has a bachelor degreee	0.16	0.19	0.19	0.22
bachelorplus	Dummy=1 if has a higher than bachelor degree	0.10	0.17	0.13	0.17
dcity	Dummy=1 if resident of a city	0.62	0.80	0.61	0.79
direg	Dummy=1 if resident of an Inner Regional Area	0.26	0.13	0.26	0.15
dremote	Dummy=1 if resident of outer regional/remote/very remote Area	0.12	0.07	0.13	0.06
occup	Dummy=1 if working in a "white collar" occupation	0.57	0.60	0.85	0.85
manufact	Dummy=1 if working in a manufacturing industry	0.16	0.15	0.04	0.08
services	Dummy=1 if working in the services industry	0.65	0.68	0.88	0.85
constru	Dummy=1 if working in the construction industry	0.09	0.09	0.02	0.01
mining	Dummy=1 if working in the mining industry	0.03	0.01	0.00	0.00
agric	Dummy=1 if working in the agricultural industry	0.03	0.01	0.01	0.01
dhelp	Dummy=1 if has access to help from others	0.61	0.61	0.65	0.63
dlsclub	Dummy=1 if active member of a community based association	0.40	0.34	0.34	0.32
dvol	Dummy=1 if do hs of volunteer work	0.16	0.13	0.22	0.21
dsocal	Dummy=1 if time socializing with friend/relatives above average	0.67	0.62	0.71	0.63
dlsfriend	Dummy=1 if declare to have a lot of friends	0.46	0.47	0.55	0.56
commsatis	Dummy=1 if satisfied with local community participation	0.73	0.70	0.76	0.73
Observations		2,078	620	2,079	584

Table 3: Pooled Logit and Random Effect Logit Models - Probability of Employment by gender

	POOLED LOGIT MODEL		RE LOGIT MODEL	
	MARGINAL EFFECTS			
VARIABLES	**MEN**	**WOMEN**	**MEN**	**WOMEN**
Migrant NESC	**0.007031****	**-0.003591**	**0.0031418**	**-0.0042207**
	(0.003413)	(0.004459)	(0.002583)	(0.003369)
Migrant ESC	**0.01053*****	**0.008157***	**0.0063262****	**0.0027447**
	(0.003565)	(0.004236)	(0.003175)	(0.004527)
Age	**-7.699e-04**	**-0.003262*****	**-0.0004513**	**-0.00257*****
	(0.001049)	(0.001013)	(0.000651)	(0.000861)
Children 14 or younger	**-0.001196**	**-0.008703*****	**-0.0005299**	**-0.00675*****
	(0.002189)	(0.002150)	(0.001143)	(0.001693)
Married	**0.02205*****	**0.02047*****	**0.00694*****	**0.010285*****
	(0.003145)	(0.002579)	(0.001454)	(0.001821)
Education: less than year 12	**-0.02740*****	**-0.009808*****	**-0.01029*****	**-0.00887*****
	(0.003328)	(0.002447)	(0.00182)	(0.001887)
Experience	**0.003774*****	**0.006160*****	**0.001978*****	**0.004676*****
	(4.300e-04)	(3.958e-04)	(0.00037)	(0.00052)
English ability	**0.02180*****	**0.01350****	**0.007039****	**0.005527**
	(0.008344)	(0.006305)	(0.00273)	(0.003623)
Index of Socia Capital	**0.006291*****	**0.005194*****	**0.002544*****	**0.002491*****
	(7.425e-04)	(8.029e-04)	(0.000544)	(0.00066)
Social Capital NESC	**-0.006046*****	**1.435e-04**	**-0.0028****	**0.001339**
	(0.002067)	(0.001959)	(0.001141)	(0.001548)
Social Capital ESC	**-0.003326**	**0.002979**	**-0.00154**	**0.00164**
	(0.002057)	(0.002347)	(0.001161)	(0.001746)
Observations	20,927	21,206	20,927	21,206
pseudo R2	0.1396	0.1437		
LR Chi2			479.97	387.09
Prob >chi2			0.0000	0.0000

Notes: (i) The Index of Social Capital includes five dummy variables as indicators of: active membership to sporting, hobby, community based club or association (dlsclub), frequency of contacts (dsocal), exchange of help (dhelp), control and satisfaction with life (commsatis) and doing favours and viceversa (dlsfriend)
(ii) ESC stands for English speaking countries and NESC for non-English speaking countries
(iii) Standard errors in parentheses
(iv) *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Random Effect Logit Model – Probability of Employment

	ALL		MEN		WOMEN	
VARIABLES	**Coeff**	**Mg Eff**	**Coeff**	**Mg Eff**	**Coeff**	**Mg Eff**
Migrant NESC	**-0.1015**	**-0.0009173**	**0.4310**	**0.0031418**	**-0.2841**	**-0.0042207**
	(0.2173)	(0.0019614)	(0.3486)	(0.002583)	(0.2697)	(0.003369)
Migrant ESC	**0.3958**	**0.0035757**	**0.8678****	**0.0063262****	**0.2200**	**0.0027447**
	(0.2765)	(0.0025244)	(0.4188)	(0.003175)	(0.3613)	(0.004527)
Age	**-0.2149*****	**-0.00194*****	**-0.06190**	**-0.0004513**	**-0.2058*****	**-0.00257*****
	(0.05313)	(0.0005077)	(0.08897)	(0.000651)	(0.06629)	(0.000861)
Children 14 or younger	**-0.3513*****	**-0.00317*****	**-0.07270**	**-0.0005299**	**-0.5407*****	**-0.00675*****
	(0.09890)	(0.0009187)	(0.1566)	(0.001143)	(0.1296)	(0.001693)
Married	**0.9035*****	**0.008162*****	**0.8497*****	**0.00694*****	**0.8245*****	**0.010285*****
	(0.09749)	(0.0011242)	(0.1553)	(0.001454)	(0.1237)	(0.001821)
Education: less than year 12	**-0.9479*****	**-0.00856*****	**-1.4116*****	**-0.01029*****	**-0.7112*****	**-0.00887*****
	(0.1113)	(0.0011815)	(0.1732)	(0.00182)	(0.1421)	(0.001887)
Experience	**0.3466*****	**0.003132*****	**0.2713*****	**0.001978*****	**0.3749*****	**0.004676*****
	(0.02247)	(0.0003117)	(0.03958)	(0.00037)	(0.02789)	(0.00052)
English ability	**0.6047*****	**0.005463*****	**0.9655*****	**0.007039****	**0.4430**	**0.005527**
	(0.2238)	(0.0020862)	(0.3482)	(0.00273)	(0.2859)	(0.003623)
Index of Social Capital	**0.2799*****	**0.002529*****	**0.3490*****	**0.002544*****	**0.1997*****	**0.002491*****
	(0.03681)	(0.0004025)	(0.05568)	(0.000544)	(0.04834)	(0.00066)
Social Capital NESC	**-0.1197**	**-0.0010817**	**-0.3840*****	**-0.0028****	**0.1073**	**0.001339**
	(0.09601)	(0.000873)	(0.1480)	(0.001141)	(0.1241)	(0.001548)
Social Capital ESC	**-0.03165**	**-0.0002859**	**-0.2114**	**-0.00154**	**0.1314**	**0.00164**
	(0.1044)	(0.0009438)	(0.1560)	(0.001161)	(0.1395)	(0.001746)
Constant	**6.6495*****		**5.0607*****		**6.0114*****	
	(0.9862)		(1.5973)		(1.2430)	

Wald Test -Coeficient for the linear combination of index and NESC and ESC

	Coeff	St. Error	Coeff	St. Error	Coeff	St. Error
ESC (Index + Social Capital ESC jointly)	**0.248****	0.0977	**-0.350**	0.126	**0.307*****	0.130
NESC (Index + Social Capital NESC jointly)	**0.160***	0.088	**0.138**	0.113	**0.331****	0.114

Observations	42,133		20,927	20,927	21,206	21,206
LR Chi2			479.97	479.97	387.09	387.09
Prob >chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: (i) The Index of Social Capital includes five dummy variables as indicators of: active membership to sporting, hobby, community based club or association (dlsclub), frequency of contacts (dsocal), exchange of help (dhelp), control and satisfaction with life (commsatis) and doing favours and viceversa (dlsfriend)

(ii) ESC stands for English speaking countries and NESC for non-English speaking countries

(iii) Standard errors in parentheses

(iv) *** p<0.01, ** p<0.05, * p<0.1

Table 5: Pooled Logit and Random Effect Logit Models for the probability of employment - "white collar" and "blue collar" occupations

	POOLED LOGIT MODEL		RE LOGIT MODEL	
	MARGINAL EFFECTS			
VARIABLES	**White Collar**	**Blue Collar**	**White Collar**	**Blue Collar**
Migrant NESC	**0.01008**	**3.189e-04**	**-0.0596748*****	**0.0327839****
	(0.01113)	(0.01061)	(0.0177955)	(0.0138704)
Migrant ESC	**0.1120*****	**-0.08781*****	**0.0670263*****	**-0.058896*****
	(0.01091)	(0.01022)	(0.0213493)	(0.0167811)
Male	**-0.2979*****	**0.2733*****	**-0.3949884*****	**0.3052232*****
	(0.004615)	(0.004377)	(0.0169329)	(0.0164633)
Age	**-0.01876*****	**-0.002974**	**-0.004801**	**-0.013149*****
	(0.003125)	(0.003024)	(0.0047105)	(0.0037022)
Children 14 or younger	**-0.008705***	**-0.002154**	**-0.0087218**	**-0.0048722**
	(0.005141)	(0.004733)	(0.0066156)	(0.0050751)
Married	**0.07588*****	**-0.03831*****	**0.0367438*****	**-0.0129257****
	(0.005842)	(0.005334)	(0.0075186)	(0.0058017)
Education: less than year 12	**-0.2318*****	**0.1982*****	**-0.2632482*****	**0.1656226*****
	(0.006380)	(0.006176)	(0.0094742)	(0.0079587)
Experience	**0.01752*****	**0.001350**	**0.0173908*****	**0.0040958****
	(0.001278)	(0.001291)	(0.0022293)	(0.0017256)
English ability	**0.1159*****	**-0.08384*****	**0.0472982*****	**-0.0363473*****
	(0.01545)	(0.01443)	(0.0148242)	(0.0116526)
Index of Socia Capital	**0.03024*****	**-0.02006*****	**0.0090336*****	**-0.0027867**
	(0.002005)	(0.001843)	(0.0024504)	(0.0018786)
Social Capital NESC	**-0.01017***	**0.006072**	**0.0069775**	**-0.0077678**
	(0.005794)	(0.005362)	(0.0067117)	(0.0052246)
Social Capital ESC	**-0.006889**	**0.005741**	**-0.0026905**	**0.0038584**
	(0.005822)	(0.005389)	(0.0069664)	(0.0054919)
Observations	42,133	42,133	42,133	42,133
pseudo R2	0.1332	0.1332		

Notes: (i) The Index of Social Capital includes five dummy variables as indicators of: active membership to sporting, hobby, community based club or association (dlsclub), frequency of contacts (dsocal), exchange of help (dhelp), control and satisfaction with life (commsatis) and doing favours and viceversa (dlsfriend)
(ii) ESC stands for English speaking countries and NESC for non-English speaking countries
(iii) Standard errors in parentheses
(iv) *** p<0.01, ** p<0.05, * p<0.1

Table 6: Fixed Effect, Random Effect and Hausman-Taylor estimation of the log of hourly wages

VARIABLES	Fixed Effect	Random Effect	HAUSMAN TAYLOR
Age	**0.08336*** **	**0.01188*** **	**0.05525*** **
	(0.006021)	(0.004329)	(0.005634)
Children 14 or younger	**7.233e-05**	**0.001339**	**-0.002948**
	(0.006155)	(0.005709)	(0.005647)
Married	**-0.001419**	**0.03261*** **	**0.01170**
	(0.007974)	(0.006853)	(0.007143)
Education: less than year 12	**-0.04966**	**-0.5190*** **	**-0.4274*** **
	(0.03307)	(0.01492)	(0.02144)
Tenure with current employer	**7.011e-04**	**0.003439*** **	**0.002049*** **
	(4.406e-04)	(3.936e-04)	(4.004e-04)
White collar occupation	**0.01297* **	**0.05196*** **	**0.03042*** **
	(0.007546)	(0.006778)	(0.006837)
Social capital Index	**0.003026**	**0.004842** **	**0.003705* **
	(0.002202)	(0.002108)	(0.002032)
Social capital ESC	**-0.003763**	**-0.005389**	**-0.003552**
	(0.006379)	(0.006036)	(0.005871)
Social capital NESC	**-0.009116**	**-0.003118**	**-0.006663**
	(0.006334)	(0.006051)	(0.005843)
Experience	**0.003647**	**0.01572*** **	**0.01051*** **
	(0.003314)	(0.002106)	(0.003092)
Migrant ESC		**-0.04054*** **	**-0.08944*** **
		(0.01536)	(0.02917)
Migrant NESC		**-0.08482*** **	**-0.1083*** **
		(0.01521)	(0.02875)
Constant	**0.3107*** **	**2.5927*** **	**1.3067*** **
	(0.1071)	(0.07579)	(0.09882)
Observations	40,595	40,595	40,595
sigma_u	0.7283	0.3899	0.8354
sigma_e	0.2804	0.2804	0.2804
rho	0.8709	0.6591	0.8988

Notes: (i) The Index of Social Capital includes five dummy variables as indicators of: active membership to sporting, hobby, community based club or association (dlsclub), frequency of contacts (dsocal), exchange of help (dhelp), control and satisfaction with life (commsatis) and doing favours and viceversa (dlsfriend)
(ii) ESC stands for English speaking countries and NESC for non-English speaking countries
(iii) Standard errors in parentheses
(iv) *** p<0.01, ** p<0.05, * p<0.1

Table 7: Fixed Effect, Random Effect and Hausman-Taylor estimation of the log of hourly wages by gender

	MEN			WOMEN		
VARIABLES	HT	FE	RE	HT	FE	RE
Age	**0.06851*** **	**0.07698*** **	**0.01714** **	**0.04708*** **	**0.07803*** **	**0.007362**
	(0.01043)	(0.01109)	(0.007742)	(0.007351)	(0.007947)	(0.005466)
Children 14 or yonger	**-0.009301**	**-0.007093**	**-0.001760**	**0.004523**	**0.007272**	**0.002696**
	(0.007655)	(0.008242)	(0.007950)	(0.008404)	(0.009259)	(0.008233)
Married	**0.008529**	**-0.006625**	**0.02713*** **	**0.02147** **	**0.007257**	**0.03749*** **
	(0.009854)	(0.01080)	(0.009862)	(0.01040)	(0.01185)	(0.009477)
Education: less than year 12	**-0.2674*** **	**0.01093**	**-0.4901*** **	**-0.4812*** **	**-0.1066** **	**-0.5070*** **
	(0.03337)	(0.04726)	(0.02390)	(0.02849)	(0.04702)	(0.01900)
Tenure with current employer	**0.001506*** **	**3.382e-04**	**0.002099*** **	**0.003143*** **	**0.001328* **	**0.005465*** **
	(5.100e-04)	(5.562e-04)	(5.125e-04)	(6.306e-04)	(6.997e-04)	(6.042e-04)
White collar occupation	**0.01458* **	**0.001486**	**0.03329*** **	**0.06116*** **	**0.03606*** **	**0.08723*** **
	(0.008073)	(0.008801)	(0.008247)	(0.01215)	(0.01355)	(0.01169)
Social capital Index	**0.001374**	**2.825e-04**	**0.003708**	**0.005814* **	**0.005950* **	**0.005732* **
	(0.002744)	(0.002948)	(0.002894)	(0.002992)	(0.003268)	(0.003036)
Social capital ESC	**-0.008949**	**-0.007159**	**-0.01397* **	**0.003935**	**6.463e-04**	**0.006382**
	(0.007769)	(0.008372)	(0.008122)	(0.008833)	(0.009663)	(0.008910)
Social capital NESC	**-0.004187**	**-0.007323**	**-9.222e-04**	**-0.008367**	**-0.01138**	**-0.006851**
	(0.008017)	(0.008625)	(0.008426)	(0.008474)	(0.009251)	(0.008609)
Experience	**-0.01069**	**0.008931**	**0.01344*** **	**0.01517*** **	**0.003535**	**0.01450*** **
	(0.006188)	(0.006750)	(0.003988)	(0.003849)	(0.004152)	(0.002625)
Migrant ESC	**-0.1106*** **		**-0.05200** **	**-0.08883** **		**-0.03302**
	(0.04205)		(0.02270)	(0.04020)		(0.02059)
Migrant NESC	**-0.1897*** **		**-0.1211*** **	**-0.07950** **		**-0.05900*** **
	(0.04337)		(0.02334)	(0.03804)		(0.01968)
Constant	**0.9257*** **	**0.4006** **	**2.4872*** **	**1.6158*** **	**0.3706** **	**2.7260*** **
	(0.1703)	(0.1814)	(0.1283)	(0.1317)	(0.1482)	(0.09831)
Observations	20,218	20,218	20,218	20,377	20,377	20,377
sigma_u	0.8722	0.7445	0.4216	0.7905	0.6995	0.3540
sigma_e	0.2647	0.2648	0.2648	0.2947	0.2949	0.2949
rho	0.9157	0.8877	0.7171	0.8780	0.8491	0.5903

Notes: (i) The Index of Social Capital includes five dummy variables as indicators of: active membership to sporting, hobby, community based club or association (dlsclub), frequency of contacts (dsocal), exchange of help (dhelp), control and satisfaction with life (commsatis) and doing favours and viceversa (dlsfriend)
(ii) ESC stands for English speaking countries and NESC for non-English speaking countries
(iii) Standard errors in parentheses
(iv) *** p<0.01, ** p<0.05, * p<0.1

APPENDIX A

PRINCIPAL COMPONENT ANALYSIS: Theory and Results

The central idea of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables.

The following tables show the results for our study using five indicators taken from the HILDA Survey to construct the index of social capital.

Table B.1: Pearson Correlation Coefficients between social capital variables

Correlation coefficients between indicators of social capital					
	dlsclub	dlsfriend	dsocal	commsatis	dhelp
dlsclub	1				
dlsfriend	0.1159	1			
dsocal	0.2031	0.2164	1		
commsatis	0.2169	0.1427	0.2347	1	
dhelp	0.1489	0.1931	0.4127	0.2387	1

Table B.2: Results from the principal component analysis (PCA)

			PRINCIPAL COMPONENTS				
			FIRST	SECOND	THIRD	FOURTH	FIFTH
			PC_{1t}	PC_{2t}	PC_{3t}	PC_{4t}	PC_{5t}
Eigenvalue			**1.508**	**0.971**	0.927	0.840	0.751
Cumulative percentage of eigenvalues			30.170	49.600	68.160	76.320	100.00
Components weights:	dlsclub	(x_{1t})	0.366	0.668	-0.360	0.537	0.011
	dlsfriend	(x_{2t})	0.554	-0.255	-0.053	-0.078	-0.786
	dsocal	(x_{3t})	0.451	-0.336	-0.589	-0.295	0.497
	commsatis	(x_{4t})	0.407	0.498	0.456	-0.595	0.153
	dhelp	(x_{5t})	0.433	-0.354	0.558	0.513	0.332

The eigenvalue for a principal component indicates the variance that it accounts for out of the total variance of 5 (sum of the diagonal terms in the correlation matrix). Thus, the first principal component in our case accounts for 30.17% (1.508/5) of the total variance which is far more important than any of the others. The eigenvectors are shown in table B.2 which in turn provide the coefficients of the principal components.

Base on the previous results (tables B.1 and B.2) the first principal component or our index of social capital is constructed as follows:

$$PC_{1t} = 0.366X_{1t} + 0.554X_{2t} + 0.451X_{3t} + 0.407X_{4t} + 0.433X_{5t}$$

In our example, the first principal component accounts only for 30.17% of the variation in the data, which is arguable not too much and we would need to take into account more than one component. It is a matter of judgement as to how many components are important but it can be argue that only the components with eigenvalues greater than one should be considered because they are the ones with variances greater than the variances of the individual standardized X_{it} variables, on other words, they account for more variation than any of the original X_{it} variables. (Manly, 2004).

REFERENCES

Aguilera, M. B., & Massey, D., S. (2003). “Social capital and the wages of Mexican migrants: new hypotheses and tests. *Social Forces, 82*(2), 671-701.

Baltagi, B. (2009). *Econometric Analysis of Panel Data* (4th ed.). UK.

Bourdieu, P. (1993). *Sociology in Question*. London.

Brook, K. (2005). Labour Market Participation: the influence of social capital. *Office for National Statistics UK - Special Feature*, 113-123.

Calvo-Armengol, & Zenou, Y. (2005). Job matching, social network and word-of-mouth communication. *Journal of Urban Economics, 57*, 500-522.

Calvo-Armengol, A., and Jackson, M. (2004). The effect of Social Networks on Employment and Inequality. *The American Economic Review, 94*(3), 426-454.

Cameron, C., A, & Trivedi, P., K. (2010). *Microeconometrics using Stata: Revised Edition*. Texas 77845 USA: Stata Press.

Chamberlain, G. (1980). Analysis of covariance with qualitative data. *Review of Economic Studies, 47*, 225-238.

Chiswick, B. (1978). The Effect of Americanization on the Earnings of Foreign-Born Men *Journal of Political Economy, 86*(5), 897-921.

Coleman, J. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, S95-S120.

Deri, C. (2005). Social Networks and Health Services Utilization. *Journal of Health Economics, 24*, 1076-1107.

Derrick, T. (2011). Personal networks and the economic adjustment of immigrants. On *Canadian Social Trends*.

Drever, A., & Hoffmeister, O. (2008). Immigrants and Social Networks in a Job-Scarce Environment: The Case of Germany. *International Migration Review, 42*(2), 425-448.

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology, 78*(6), 1360-1380.

Hausman, J., & Taylor, W. (1981). Panel data and unobservable individual effects. *Econometrica, 49*(6), 1377-1398.

Herreros, F. (2004). *The Problem of Forming Social Capital: Why Trust?* . New York and Houndmills: Palgrave Macmillan.

Hu, X., Kaplan, S., & Dalal, R., S. (2010). An examination of blue- vs white-collar workers' conceptualizations of job satisfaction facets. *Journal of Vocational Behaviour, 76*, 317-325.

Ioannides, Y., M., & Loury, L. (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature, 42*(4), 1056-1093.

Labini, M. (2004). Social Networks and Wages: It's all about connections! *LEM Papers Series 2002/18*. Pisa, Italy: Laboratory of Economic and Management (LEM), Sant'Anna School of Advanced Studies.

Lancee, B. (2010). The economic returns of immigrants' bonding and bridging social capital: the case of the Netherlands. *International Migration Review, 44*(1), 202-226.

Lin, N. (1999). "Social networks and status attainment. *Annual Review of Sociology, 25*, 467-487.

Loury, G. (1977). A dynamic theory of racial income differences. In P. A. Wallace, and LaMonde, A, M (Ed.), *Women, Minorities and Employment Discrimination*: Lexington, MA: Lexington Books.

Manly, B., F, J. (2004). *Multivariate Statistical Methods. A Primer* (2nd ed.). London: Chapman and Hall.

Montgomery, J., D. (1991). Social networks and labor-market outcomes: toward and economic analysis. *American Economic Review, 81*, 1401-1418.

Mouw, T. (2003). “Social capital and finding a job: do contacts matter? *American Sociological Review, 68*(6), 868-898.

Pearson, Q. (1998). Job satisfaction, leisure satisfaction, and psychological health. *Career Development Quarterly, 46*, 416-426.

Putnam, R., D , Leonardi, R., & Nanetti, R. (1993). *Making Democracy work: Civic Traditions in Modern Italy*. Princeton: Princeton University Press.

Rosenbaum, J., DeLuca, S., Miller, S., & Roy, K. (1999). Pathways into work: Short and long-term effects of personal and institutional ties. *Sociology of Education, 72*(3), 179-196.

Sabatini, F. (2009). The Labour Market. In G. Svendsen (Ed.), *Handbook of Social Capital* (pp. 445). UK: Edward Elgar Publishing Limited.

Staiger, D., & Stock, J. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65*(3), 557-586.

Stone, W., Gray, M., & Hughes, J. (2003). Social Capital at Work: how family, friends and civis ties relates to labour market outcomes *Research Paper No 31*. Melbourne, Australia: Australian Institute of Families Studies.

Summerfield, M., Freidin, S., Hahn, M., Ittak, P., Li, N., Macalalad, N., . . . Wooden, M. (Eds.). (2012). *HILDA User Manual - Release 11*. Melbourne, Australia: Melbourne Institute of Applied Economic and Social Research - University of Melbourne.

Sun, Y. (1999). The contextual effects of community social capital on academic performance. *Social Science Research, 28*(4), 403-426.

Toppinen-Tanner, S., Kalimo, R., & Mutanen, P. (2002). The process of burnout in white-collar and blue-collar jobs: Eight-year prospective study of exhaustion. *Journal of Organizational Behaviour, 23*, 555-570.

Xue, L. (2008). *Social Capital and Employment Entry of Recent Immigrant to Canada*. Canada: Citizen and Immigration Canada.