Immigrant Networks in Australia: Do They Help Newly Arrived Immigrants to Find Jobs and Get Higher Income?

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Abstract Using data from the 2006 Census survey this paper examines the presence of immigrant network effects in the Australian labor market. We focus on four relatively important immigrant groups. Namely British, Chinese, Indian and Filipino. We analyze the impact of these networks on employment and income outcomes of newly arrived immigrants. The evidence suggests that these networks help immigrants from the UK in terms of employment probability and average income. However, the presence of a Chinese network results in lower probability of being employed and a lower incomes for recent Chinese immigrants. The presence of Indian and Filipino networks do not appear to have a statistically significant impact on employment probability and income outcomes on the immigrants from those two countries.

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1 Introduction

According to the 2006 Census, every fifth Australian resident was born abroad. Moreover this proportion has remained roughly constant from 1991 through 2006 (see Table 1). However, while the proportion of immigrants has remained relatively stable, the composition of the immigrant pool has changed. For example, Miller and Neo (1998) document that immigration in Australia historically had been dominated by immigrants of British and European origins. However, due to changes in Australian immigration policy, combined with changes in economic and political circumstances in the countries of potential immigrants, there has been an increasing trend in Asian immigration. This changing composition of immigrant provides an unique opportunity to evaluate the role of immigrant networks and if their impact varies depending on the nature of the home country.

In 1973 the Australian government adopted a migration policy of non-discrimination on the grounds of race, color or nationality. However, since the late 1980's the policy has focused on skilled immigration. For example, to simplify the entry of temporary skilled workers, their duration of stay was extended to four years in 1996. However, the unemployment rate of skilled migrants became an issue of major concern in the mid-90s, resulting in two major policy changes. First, since 1999, it has been mandatory for potential skilled migrants to have their capabilities recognized as equivalent to those of Australians by Australian professional or trade institutions prior to filing an application for migration. Second, since 2001, foreign graduates of Australian universities has been allowed to apply for immigrant status without leaving Australia or gaining relevant work experience. These policies might have induced compositional changes of Australian immigration.

Table 1 indicates that the composition of immigration has changed dramatically since 1991. The share of immigrants from Western countries has been declining steadily since 1991. For example, the share of Greeks decreased from 3.4 to 2.6 percent, Italians - from 6.9 to 4.5 percent, the British - from 31.3 to 23.6 percent from 1991 to 2006. In contrast, the proportion of immigrants from South and East Asia has significantly increased. For instance, the share of Chinese increased from 2.0 to 4.7 percent, Indians - from 1.7 to 3.4, and Filipinos - from 1.8 to 2.8 percent between 1991- 2006 [1] .

Given the change in immigration composition a natural question that arises is how these new immigrants assimilate in Australia. Do Asians face more limited employment opportunities than Western Europeans? Do they have similar incomes as their European peers? And do ethnic networks help to facilitate the transition of new immigrants into the Australian labor market?

To address these questions we focus on four important ethnic groups. Namely the British, Chinese, Filipino and Indian. We assume that immigrants that come from the same country and who are located in the same geographical area are likely to have a relatively higher propensity to network (interact). We then evaluate impact of network effects on employment opportunities and incomes of recently arrived immigrants. Section 2 presents a literature review on immigrant networks focusing on the Australian experience. Section 3 provides a model which might explain the differences in labor market outcomes of newly arrived immigrants of different ethnic backgrounds. Section 4 discusses the data and descriptive statistics. Section 5 reports some empirical results and section 6 concludes.

2 Literature

The concept of a "network" is widely used both in economics and sociology. While this term is well studied and defined in sociology, in economics the definition is less strict and often depends on the purpose of the particular study. Ioannides and Datcher Loury (2004) provide an excellent survey of literature on networks from both perspectives. Following Kortum (2003), they define a network as a "personalized exchange among many agents". Here we use a more narrow definition of a network. We assume that immigrants of the same ethnicity who live in the same area are more likely to interact, and, therefore, belong to the same network. Ioannides and Datcher Loury (2004) also identify a few stylized facts that

[1]Note changes are even more dramatic if we focus only on 15-64 year old immigrants.

are useful for our analysis. They document that the use of networks to search for jobs has increased over time, but it varies by location and demographic characteristics.

Calvó-Armengol and Jackson (2007) develop a theoretical model about network impacts on wage and employment dynamics and inequality. They show that networks in general improve an individual's probability of employment and wage level. However, under some conditions both may decline. Calvó-Armengol and Jackson (2004) establish a positive correlation in employment of agents within the same network and explain how this might result in employment inequality between different networks.

The empirical evidence largely supports a positive impact of networks on labor market outcomes of immigrants. Munshi (2003) finds that Mexican migrants in the United States that belong to larger networks are more likely to be employed and to have higher nonagricultural wages. Patel and Vella (2007) find that recent immigrants in the US tend to choose the same occupation as their countrymen. Moreover, individuals that choose the most "popular" occupation within their ethnic network have higher wages than those that do not. Beaman (2009), considering networks of resettled refugees, finds that an increase in the number of social network members has a negative impact on labor market outcomes, whereas a greater number of tenured network members improves the probability of employment and increases wage. Dustman et al. (2009), using German employer-employee matched data, find that workers from minority groups are more likely to work with workers from the same minority group than with workers from other minority or majority groups. Moreover, they show that ethnic minority workers earn higher wages and are less likely to leave their jobs if they are working in a firm with a large percentage of workers from the same minority.

There is extensive literature on immigrant labor outcomes in Australia. Miller and Neo (1998), summarizing studies on employment and unemployment in Australia, document that immigrants experience higher unemployment rates than natives. They also find that unemployment rates are lower for immigrants from English speaking countries than for those from non-English speaking ones. Moreover, immigrants from English speaking countries have marginally lower unemployment rates than those who are Australian-born. Miller and Neo (1998) also identify main reasons for why unemployment rates for immigrants might be lower than for natives. First, foreign human capital might not be fully transferrable to the Australian labor market. Second, immigrants may be less proficient in English and, therefore, face limited job prospects. Third, natives may have more information about job opportunities than immigrants. Finally, immigrants may face discrimination from employers.

Recent studies provide some support to these claims. For example, Chiswick and Miller (2008) provide empirical evidence of the limited transferability of foreign human capital. They show that immigrants start off with a relatively lower status occupation when they first enter the Australian labor market. Moreover, they show that returns to education for immigrants from non-English speaking countries are lower than for those from English speaking countries or for natives. Chiswick and Miller (2009), using the overeducation / required education / undereducation (ORU) framework, link overeducation to the imperfect international transferability of immigrants' schooling, and undereducation to self-selection into immigration. Chiswick and Miller (2000) find that linguistic enclaves reduce the acquisition of English skills among immigrants. They also find that the apprehension Australians feel towards multiculturalism is because they see it as a mechanism for separate cultural preservation. Since language is a salient feature of any culture, linguistic enclaves are conducive to separate culture preservation. Thus, belonging to an ethnic enclave or network might lead to some form of discrimination against new immigrants. On the other hand, the authors find that Australians have more favorable attitudes towards immigrants from non-English speaking backgrounds who have better English proficiency.

Our paper contributes to the existing literature by studying the differences in labor market outcomes between four ethnic networks. British immigrants represent a fairly well-established old network which linguistically is the most similar to natives, and thus should not face barriers associated with language. Chinese, Filipino and Indians are relatively younger immigration waves. Since those groups are very distinct from the natives, and English is not a native language for the most members, issues related to language might arise.

3 The model

We now present a model which shows that under some conditions we can expect reservation wages decline with increase in network size. We extend Flabbi (2009) search-matching-bargaining model by including the network size effect [2]. Also we take into account Chiswick and Miller (2000) findings that Australians feel apprehension towards multiculturalism and that size of the linguistic enclave reduces English skills acquisition. We interpret it as some employers might be sensitive to non-English speaking immigrants. This sensitivity can arise for a number of reasons. To name a few, employers may think that non-English speaking employees are less capable to interact with other workers or clients than English speaking employees, or that they will have harder time to understand work instructions and rules, or, due to ethnic differences, they will not fully embrace corporate culture and will not be good team-players, etc.

Suppose we have two types of workers (English speaking immigrants and non-English speaking immigrants) and two types of employers (sensitive and non-sensitive). Workers continuously search for jobs, they meet employers according to Poisson process with instantaneous arrival rate λ. We assume that λ positively depends on the size of the network, n. That is, each individual can search independently from her network through newspapers, internet, etc. Also she can learn about jobs opportunities from her network. We assume the larger the network the more information about job offers will be transmitted to a worker. There is no on-the-job search. A worker meets a sensitive employer with probability p and a non-sensitive employer with probability $(1 - p)$. Once worker and employer meet, they observe a match specific productivity (x) which is drawn from an exogenous distribution $G(x)$. Wages are determined by Nash bargaining once productivity is observed. Match can

[2] We will not try to estimate this model structurally due to the data limitations. This model serves solely demonstrational purposes.

be terminated by Poisson process at exogenous rate δ. When unemployed, workers received utility (disutility) b. Workers and employers discount at the same rate r.

English and non-English speaking workers are denoted $J = E, NE$; whereas, language sensitive and non-sensitive employers are denoted $I = S, NS$. The value function for the employed worker of type J working for the employer of type I at wage $w_{IJ}(x)$ is

$$(r+\delta)W_J(w_{IJ}(x)) = w_{IJ}(x) + \delta U_I \tag{1}$$

The value function for the unemployed worker of type J is

$$\begin{aligned} U_J = b + \lambda(n)[p \int max(W_J(w_{SJ}(x)) - U_J, 0)dG(x) + \\ +(1-p)\int max(W_J(w_{NSJ}(x)) - U_J, 0)dG(x)] \end{aligned} \tag{2}$$

Employers have linear profit functions. Sensitive employers experience disutility, d, from hiring non-English speaking immigrant which positively depends on the size of the network.

$$\Pi_{IJ}(x) = \begin{cases} x - d(n) - w & \text{if} \quad I = S, J = NE \\ x - w & \text{if} \quad \text{o/w} \end{cases} \tag{3}$$

Given this profit function, a value of filled job is

$$F_{IJ}(w) = \frac{\Pi_{IJ}(w)}{r+\delta} \tag{4}$$

Wages are determined by Nash bargaining

$$w_{IJ}(x, U_J) = arg \max_w [(W_J(w) - U_J)^\alpha F_{IJ}(w)^{1-\alpha}] \tag{5}$$

After taking log and first order conditions, we can obtain

$$w_{IJ} = \alpha(1 - d(n)I_{(SNE)}) + (1 - \alpha)rU_J \tag{6}$$

where $I_{(SNE)}$ is an indicator function equal to one when worker is non-English speaking and employer is language sensitive. Thus, we obtain the following wage schedules:

- English speaking immigrants

$$w_{iE} = \alpha x + r(1 - \alpha)U_E \tag{7}$$

- Non-English speaking immigrants that meet non-sensitive employers

$$w_{NSNE} = \alpha x + r(1 - \alpha)U_{NE} \tag{8}$$

- Non-English speaking immigrants that meet sensitive employers

$$w_{SNE} = \alpha(x - d(n)) + r(1 - \alpha)U_{NE} \tag{9}$$

Therefore, if unemployment value functions are the same for English speaking and non-English speaking immigrants, both groups have exactly the same wage if they meet non-sensitive employer. However, if they meet sensitive employer the wage differential is:

$$w_{SE} - w_{NSNE} = \alpha d(n) + r(1 - \alpha)(U_E - U_{NE}) \tag{10}$$

where the first term in the summation is the result of difference in sensitivity that comes from disutility that employer has from hiring non-English speakers. The second term is the result of equilibrium effect: non-sensitive employers also offer lower wages to non-English speakers if outside option for the latter is lower.

Now consider the impact of network size effect on equilibrium reservation wages. Given a vector of $(\lambda, n, \delta, r, b, \alpha, d, p)$ and $cdf\, G(x)$, define *equilibrium* as a vector of unemployment values $U^* = (U_E^*, U_{NE}^*)$ that solves

$$\begin{aligned} rU_J &= b + \frac{\lambda(n)}{r+\delta}[p\int_{rU_J+d(n)I(w,p)}(x - d(n)I(w,p) - rU_J)dG(x) + \\ &+(1-p)\int_{rU_J}(x - rU_J)dG(x)] \end{aligned} \tag{11}$$

We find that $\frac{\partial x^*(n)}{\partial n} > 0$ for English speaking immigrants and non-English speaking immigrants who match with non-sensitive employers.[3] On the other hand, we can have either positive or negative impact of network on equilibrium productivity of non-English speakers depending on parameter values.

What is the network effect on equilibrium reservation wages? From worker equilibrium condition we know that $w_J^* = rU_J$; from Nash bargaining result at the equilibrium we know that for English speakers and non-English speakers who face non-sensitive employers $w^* = x^* = rU$. On the other hand, for non-Enligh speakers who face sensitive employers $w^* = rU$ and $x^* = rU + d(n)$ or $x^* = w^* + d(n)$. Thus, $w^* = x^* - d(n)$. Taking the above into account, we obtain

- for English speakers and non-English speakers who face non-sensitive employers $\frac{\partial w^*(n)}{\partial n} > 0$
- for non-English speakers who face sensitive employers $\frac{\partial w^*(n)}{\partial n} \gtrless 0$ since $\frac{\partial w^*(n)}{\partial n} = \frac{\partial x^*(n)}{\partial n} - \frac{\partial d(n)}{\partial n}$

4 Data and key variables

Our data analysis employs the five percent sample of the 2006 Australian Census. We consider 15-64 year old immigrants who are in the labor force. We distinguish between "new"

[3]see appendix A.1 for detailed derivation.

immigrants, those who arrived within the last five years of the Census year, i.e. between 2001 and 2006, and "established" immigrants, those who arrived prior to 2001. Tables 2 - 4 provide descriptive distributional statistics for 2006 Census. The largest share of newly arrived immigrants comes from the UK - 16 percent, followed by New Zealand - 12 percent, then India and China - 10 percent each. The smallest shares come from Germany - 1.4 percent, Vietnam - 1.1 percent, Italy - 0.5 percent, and Greece - 0.1 percent.

It is noteworthy that 44 percent of Indians and 35 percent of Chinese in Australia came within the last five years. This fact highlights the general trend of increasing immigration from South and East Asia starting in the mid-90s. Contrastingly, shares of newly arrived immigrants [4] from Western Europe are much smaller and constitute 13, 12, 4 and 2 percent for Germany, the UK, Italy and Greece, respectively.

Our goal is to focus on relatively homogenous ethnic networks. We decided to focus on four ethnic groups: British, Chinese, Filipino, and Indian because they comprise a diverse set of ethnicities and because significant data exists for these communities [5]. We picked British as the group most similar to natives in terms of language skills, education, and other characteristics. Thus, new British immigrants might have an easier time transitioning into the Australian labor market. Chinese and Indians represent two of the largest Asian ethnic networks in terms of newly arrived immigrants in 2006. Filipinos are representative of migration from other East and South Asian countries.

The rest of the empirical analysis is based on these four groups. Thus, our final sample comprises of 1,532 observations on newly arrived immigrants, out of which 632 are British, 378 - Chinese, 112 - Filipinos, and 410 - Indians.

A local labor market and a network are identified by a statistical region. We assume that people of the same country of origin who live in the same statistical region are more likely to interact with each other. Therefore, they might be more likely to share information about

[4]Newly arrived immigrants as percentage of total immigrants from a particular country.

[5]We would like to identify more ethnic networks. However, we either had just a few observations on newly arrived immigrants or it was not possible to identify the exact country of origin since countries were aggregated up to the regional level.

new job opportunities with people from the same network. There are 48 statistical regions in our sample. Tables 5 - 8 present the top 10 location destination choices of new immigrants by statistical region and state. Most newly arrived Chinese and Indian immigrants tend to locate in the statistical regions of the Melbourne and Sydney states. Even though most of the top 10 destination choices for Filipinos are also in the Melbourne and Sydney states, some venture out to Western Australia (Lower Western Australia) and Brisbane (Brisbane city). Interestingly, for new British immigrants, most of the top 10 location choices are in Western Australia and Brisbane, and only some go to Melbourne and Sydney. In general, there is a lot of heterogeneity in location destinations.

Tables 9 - 11 report demographic characteristics of the sample. Table 9 shows that 52 percent of new immigrants from China and the Philippines are female. On the other hand, only around 41 percent of British and 34 percent of Indian immigrants are female. The gender composition of established immigrants is quite different from new immigrants. Females represent larger share of Filipino migrants, 59 percent. However, for the rest of the groups, males dominate with 56, 53 and 59 percent among British, Chinese and Indian immigrants, respectively.

Table 10 present age distributions of new and established immigrants in four ethnic groups. Newly arrived immigrants from China and India tend to be young, 52 and 56 percent respectively are below age 30. In comparison, new immigrants from the Philippines and the UK are more mature, 57 and 59 percent respectively are between 30-44 years old. Among established immigrants, Brits are represented by a higher proportion of older people, 57 percent are between 45-64 years old. Less than half of established Chinese and Indian immigrants are in this age range: 45 and 44 percent respectively. For Filipinos, this number is only 39 percent.

Another salient feature of newly arrived immigrants from China and India is that more than 90 percent have at least a high school education [6] (see Table 11). In contrast, only 80

[6]Unfortunately, the data that we are using does not allow us to differentiate between high school and higher level of education.

percent of Brits and Filipinos completed high school or more. Among established immigrants, Chinese, Filipinos and Indians lead with 83, 83 and 84 percent respectively with high school degrees and above. However, the share of established Brits who completed high school and above is much lower - only 52 percent.

Table 12 describes self-reported fluency in English. Interestingly, only a significant share of Chinese self-reports a bad command of English: 24 percent of new and 26 percent of old immigrants. In contrast, for other ethnic groups English is not a problem: only 2 percent of Indians and 4 percent of Filipinos say that know English "not well" or "not well at all". Since this number is self-reported, its accuracy is in doubt. For this reason, we will not use it in our empirical analysis.

Labor market outcomes are measured by an individual's probability of being employed and her income. We observe employment outcomes for the whole sample of 1,532 new immigrants, but income data is available only for 1,107 individuals.

The data show that the probability of being employed in 2006 for new immigrants was the highest among British, 94 percent, followed by Filipinos, 92 percent (see Table 13) . It was much lower for Indians - 85 percent, and the lowest for Chinese - 80 percent. Newly arrived females in all four ethnic groups have on average lower employment rates than males. Chinese, Filipino and Indian women are 8 percentage points less likely to have a job, whereas for Brits this gap is only 2 percentage points. On the other hand, as immigrants settle in, the employment gap either becomes smaller (Chinese established women are only 2 percentage points less likely to have an employment than men), disappears as in the Philippines case, or women become slightly more likely to have a job as in British and Indian communities.

In general, more educated immigrants are more likely to find a job [7] (Table 14). This is true for both new and established immigrants. The only exception is newly arrived British immigrants for whom the probability of having a job with 10 years of education or less is 98 percent, but with 12 years or more is 95 percent.

[7] Note that people with 11 years of schooling violate this employment trend. However, this might be due to the fact that we have a small sample of people with exactly 11 years of education

New British immigrants on average have higher incomes than Asians (see Table 15). Mean weekly income in 2006 of a newcomer Brit was 1,015 Australian dollars (AUD), whereas for a Filipino this number was only AUD 686, and for an Indian - AUD 656. On average Chinese earned the least - AUD 455 a week. However, income distribution is different for established immigrants. Indians earn the most - AUD 1,013, followed by Brits - AUD 949, Filipinos - AUD 761. Chinese have the lowest income among established immigrants - AUD 672. Also, the mean income differentials between the highest and lowest earning groups are decreasing as immigrants settle in Australia. Women on average get lower wages than men across all ethnic groups, and both as new or established immigrants [8].

Similar to employment trends, people with higher education receive higher weekly incomes [9] (see Table 16). This fact holds true for all ethnic groups under consideration as well as for new and established immigrants.

To conclude, well known stylized facts of labor market trends can be observed from our subsample of immigrants: more educated people are doing better in terms of employment and income, there is a gender income differential, and established immigrants are performing better in terms of labor market outcomes. The latter fact might be an indication that it takes time for newly arrived immigrants to settle in the host country labor market. Therefore, ethnic networking might serve as one of the mechanisms to facilitate this transition.

5 Empirical estimation

While the descriptive statistics discussed above uncover some interesting features, we now investigate somewhat more rigorously whether ethnic networks have an impact on employment and incomes of new arrivals. Our basic specification is

[8] Note these are just descriptive statistics. We are not taking a stand on the issue of gender wage discrimination.

[9] We have similar outliers in terms of wages among people who have competed exactly 11 years of schooling.

$$Pr(I_{ijr} = 1) = \alpha + \beta Z_{jr}^{est} + X_i\gamma + \epsilon_{ijr} \tag{12}$$

where I_{ijr} is an indicator for being employed for a new immigrant i from country j who lives statistical in region r; Z_{jr}^{est} is a network measure represented by number of established immigrants from country j in statistical region r; X_i is a vector of individual characteristics which includes gender dummy, marital status and education. Finally, ϵ_{ijr} is a zero mean error term.

Columns (1) and (2) of Table 17 present Probit and OLS estimates of equation (1) respectively. In both cases there is a strong positive correlation between the probability of being employed of a newly arrived immigrant in region r and the number of established immigrants from the same country in the same region.

Estimating (1) by OLS or Probit will lead to biased estimates due to endogeneity coming from the network measure. It is possible that some unobservable characteristics, such as labor demand shocks, might impact both established immigrants' decisions about locations in statistical region r and new arrivals' employment opportunities. It is also possible, although somewhat less likely, that causality runs in the other direction. To address this issue we follow Patel and Vella (2007) and instrument Z_{jr}^{est} by Z_{jr2001}^{est}, the number of established immigrants from country j in statistical region r in 2001. The number of established immigrants from a particular country in a specific region in 2006 is strongly correlated with the same number in 2001, the correlation coefficient is 0.81. On the other hand, we assume that the unobserved characteristics mentioned above that are correlated with number of established immigrants in 2006 do not affect the number of established immigrants in 2001.

The results of IV regression pooled across four immigrant groups show that network has a positive and significant effect on the employment probability of newly arrived immigrants. Increasing the number of established immigrants from country j in region r by one thousand people is associated with a 0.42 increase in employment probability of a new immigrant from the same ethnic network (see column (3)).

In columns (4) and (5) we provide robustness checks of the model by controlling for employment rate in the state. Column (4) presents the results of OLS regression. Column (5) addresses the endogeneity issue of a regressor of main interest, size of established network, and endogeneity of the employment rate in a given state. We instrument employment rate by employment rate in a given state in 2001. Controlling for the overall employment rate in a given state attenuates the magnitude of network coefficient. However the statistical significance of the result remains.

In columns (1)-(5) we considered the general network effect. However, as motivated by theoretical framework, if one believes in language sensitivity story, we might expect some networks to be helpful and some hurtful for new members. Thus, to study impacts of a particular network on employment opportunities, we amend the model to reflect ethnically specific networks. In particular, we include the interaction of a new immigrant's country of origin and the number of established immigrants from the same country (see equation 2).

$$Pr(I_{ijr} = 1) = \alpha + \beta Z_{jr}^{est} * Pr(I_j = 1) + X_i\gamma + \epsilon_{ijr} \tag{13}$$

This decomposition unveils interesting results (columns 6 and 7). In fact, only the UK network is positively significantly associated with the employment of its new members. Increasing the size of the network by 1,000 people raises the probability of being employed for a newly arrived Brit by 0.3. On the other hand, the Chinese network "hurts" its new members in terms of employment opportunities. The correlation is positive and insignificant for Filipinos, and negative and insignificant for Indians.

Next, we estimate the impact of immigration network on income of newly arrived immigrants[10]. We are concerned about self-selection into the employment. However, due to the lack of an exclusion restriction and the endogeneity problem in both employment and income equations, we will restrict ourselves to the analysis of income conditional on employment.

[10]We estimate wage regressions only for British, Chinese and Filipino immigrants since we don't have information about wages for Indians in 2001.

The empirical model is as follows

$$w_{ijr} = \alpha + \beta Z_{jr}^{est} + X_i \gamma + \epsilon_{ijr} \tag{14}$$

where w_{ijr} is the income of employed new immigrants, Z_{jr}^{est} is a network measure represented by the number of established immigrants from country j in statistical region r or by mean income of established immigrants from country j in statistical region r. X_i is a vector of the same individual characteristics as in equation (1), and ϵ_{ijr} is a zero mean error term. As before, we are concerned about the endogeneity of network measures. Thus, we apply the same strategy as in the employment probability case by instrumenting Z_{jr}^{est} with Z_{jr2001}^{est}.

Estimation results suggest that, controlling for other characteristics, there is a strong positive correlation between wages of newly arrived immigrants and mean income of established networks (Table 18, cols 2 and 4) and number of old immigrants (Table 20, cols 2 and 4).

Similarly to employment probability, we proceed by separating results for different networks. We find a strong positive association between income of new and old immigrants for all ethnic groups (Table 19, cols 6 and 8). A one dollar increase in the mean income of established immigrants from the respective network implies an AUD 1.6 increase in income of newly arrived Brits and an AUD 1.8 increase of Chinese and Filipinos.

However, when we proxy network by the number of established immigrants from the same country, we find substantial variation in impact of different ethnic groups (Table 21, cols 6 and 8). The British network has a significant positive impact on incomes of newly arrived Brits. But the Chinese network has a strong negative effect on incomes of its new members. The Filipino network also negatively impacts the incomes of its members, however, the relationship is insignificant. These results are similar to what we have found for employment probabilities: the British network helps its new members and the Chinese network "hurts".

The empirical results seem to be supportive of Chiswick and Miller (2000) findings on linguistic enclaves. As we estimated, the British network helps its new members, whereas the Chinese network "hurts". The Chinese network is an obvious example of ethnic enclave belonging to which might reduce English proficiency. If natives apprehend the distinct ethnic enclave, this might lead to lower labor market outcomes for the members of the particular enclave. On the other hand, British are more similar in their characteristics to natives which might enhance the impact of their network.

Another possible explanation of the result might be in line with the Calvó-Armengol and Jackson (2007) model. The Chinese community might be a low equilibrium network; therefore, belonging to the network actually worsens employment and income opportunities of its new members. On the other hand, the British community is a high equilibrium network, thus, its members enjoy higher labor market outcomes.

6 Conclusion

This paper examines the immigrant networks effects in the Australian labor market. We focus on four ethnic networks: British, Chinese, Indian and Filipino. British immigrants are very similar to natives in terms of culture and English language command. Thus, one could expect that Brits have easier time assimilating in the Australian labor market than representatives of other networks. Chinese and Indian immigrants belong to the recent rapidly growing waves of immigration which are very distinct from natives. Finally, immigrants from the Philippines are representative of other Asian immigration to Australia.

We study the impact of these four networks on labor market outcomes of newly arrived immigrants. The regression analysis shows that, in general, network has a positive significant impact on the employment probability and weekly income of new members. However, when differentiating between different networks, we find a lot of heterogeneity in how a particular ethnic network affects labor market outcomes of its new members. For example, British network has a positive significant effect on the probability of being employed and weekly income of a newly arrived immigrant from the UK. On the other hand, Chinese network negatively impacts both employment probability and income of a new Chinese immigrant. Indian and Filipino networks do not affect labor market outcomes of newly arrived migrants significantly.

Thus, we document the differences in impact of ethnic networks on labor market outcomes of its' new members. Further research is needed to identify if these differences come from the fact that some employers are sensitive towards the particular ethnic groups, or that there are persistent employment opportunity and income inequalities between representatives of different ethnic networks due to the starting states of their networks.

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7 Tables

Table 1: **Proportion of immigrants by country (region) of origin in Australia**

Census years/ Country or region	1991	1996	2001	2006
Americas[a]	3.84	3.97	3.78	4.05
China[b]	2.03	3.77	3.57	4.72
Germany	2.93	2.79	2.53	2.35
Greece	3.44	3.32	2.85	2.59
India	1.68	n/a	n/a	3.38
Italy	6.89	6.14	5.02	4.48
New Zealand	7.75	7.30	8.72	8.64
North Africa and the Middle East	4.66	4.81	5.01	5.83
North-East Asia[c]	3.08	3.45	3.99	4.07
North-West Europe[d]	4.88	3.72	3.88	4.92
Oceania and Antarctica	2.04	1.96	2.53	2.46
The Philippines	1.78	2.33	2.62	2.76
South-East Asia[e]	4.97	5.44	5.99	6.03
Southern and Central Asia[f]	1.30	3.49	4.62	2.89
Southern and Eastern Europe[g]	11.90	12.59	10.79	9.30
Sub-Saharan Africa	2.49	3.02	3.61	4.45
The United Kingdom	31.33	28.97	26.45	23.60
Vietnam	3.00	2.94	4.04	3.47
Percnt imm in tot popl	22.1	21.9	21.6	22.1

[a]Canada, Caribbean, Central America, South America and USA
[b]excludes SARS and Taiwan Province
[c]excludes China
[d]excludes Germany and the United Kingdom
[e]excludes the Philippines and Vietnam
[f]excludes India in 1991 and 2006
[g]excludes Greece and Italy

Table 2: **Number of 15-64 immigrants in the labor force by country/region of origin and time of arrival**

Country/region of origin	**Established immigrants**	**New immigrants**	**Total**
Americas[a]	879	195	1,074
China[b]	715	378	1,093
Germany	389	56	445
Greece	303	5	308
India	523	410	933
Italy	494	20	514
New Zealand	1,939	465	2,404
North Africa and the Middle East	900	167	1,067
North-East Asia[c]	711	165	876
North-West Europe[d]	919	159	1,078
Oceania and Antarctica	539	104	643
The Philippines	649	112	761
South-East Asia[e]	1,205	300	1,505
Southern and Central Asia[f]	500	220	720
Southern and Eastern Europe[g]	1,611	134	1,745
Sub-Saharan Africa	833	372	1,205
The United Kingdom	4,708	632	5,340
Vietnam	811	45	856
Total	18,628	3,939	22,567

[a]Canada, Caribbean, Central America, South America and USA
[b]excludes SARS and Taiwan Province
[c]excludes China
[d]excludes Germany and the United Kingdom
[e]excludes the Philippines and Vietnam
[f]excludes India
[g]excludes Greece and Italy

Table 3: **Percentage of 15-64 immigrants in the labor force by country/region of origin and time of arrival**

Country/region of origin	**Established immigrants**	**New immigrants**	**Total**
Americas[a]	4.72	4.95	4.76
China[b]	3.84	9.6	4.84
Germany	2.09	1.42	1.97
Greece	1.63	0.13	1.36
India	2.81	10.41	4.13
Italy	2.65	0.51	2.28
New Zealand	10.41	11.81	11.65
North Africa and the Middle East	4.83	4.24	4.73
North-East Asia[c]	3.82	4.19	3.88
North-West Europe[d]	4.93	4.04	4.78
Oceania and Antarctica	2.89	2.64	2.85
The Philippines	3.48	2.84	3.37
South-East Asia[e]	6.47	7.62	6.67
Southern and Central Asia[f]	2.68	5.59	3.19
Southern and Eastern Europe[g]	8.65	3.4	7.73
Sub-Saharan Africa	4.47	9.44	5.34
The United Kingdom	25.27	16.04	23.66
Vietnam	4.35	1.14	3.79
Total	100	100	100

[a]Canada, Caribbean, Central America, South America and USA
[b]excludes SARS and Taiwan Province
[c]excludes China
[d]excludes Germany and the United Kingdom
[e]excludes the Philippines and Vietnam
[f]excludes India
[g]excludes Greece and Italy

Table 4: **Percentage of 15-64 LF immigrants by year of arrival and country/region of origin**

Country/region of origin	**Established immigrants**	**New immigrants**	**Total**
Americas[a]	81.84	18.16	100
China[b]	65.42	34.58	100
Germany	87.42	12.58	100
Greece	98.38	1.62	100
India	56.06	43.94	100
Italy	96.11	3.89	100
New Zealand	80.66	19.34	100
North Africa and the Middle East	84.35	15.65	100
North-East Asia[c]	81.16	18.84	100
North-West Europe[d]	85.25	14.75	100
Oceania and Antarctica	83.83	16.17	100
Philippines	85.28	14.72	100
South-East Asia[e]	80.07	19.93	100
Southern and Central Asia[f]	69.44	30.56	100
Southern and Eastern Europe[g]	92.32	7.68	100
Sub-Saharan Africa	69.13	30.87	100
United Kingdom	88.16	11.84	100
Vietnam	94.74	5.26	100
Total	82.55	17.45	100

[a]Canada, Caribbean, Central America, South America and USA
[b]excludes SARS and Taiwan Province
[c]excludes China
[d]excludes Germany and the United Kingdom
[e]excludes the Philippines and Vietnam
[f]excludes India
[g]excludes Greece and Italy

Table 5: **Percentage of 15-64 LF immigrants from China by year of arrival and top 10 location destinations (for new immigrants)**

State	Statistical region	New immigrants	Established immigrants	Total
New South Wales	St George-Sutherland	12.70	14.13	13.63
Victoria	Inner Eastern Melbourne	10.32	10.07	10.16
New South Wales	Lower Northern Sydney, northern beaches	8.47	8.25	8.33
New South Wales	Inner Sydney, Eastern Suburbs	6.08	5.03	5.40
New South Wales	Canterbury-Bankstown	5.56	5.87	5.76
Victoria	North Eastern Melbourne	4.76	1.96	2.93
New South Wales	Central Western Sydney	4.50	8.95	7.41
Victoria	Outer Western Melbourne	3.97	1.82	2.56
Victoria	Southern Melbourne	3.97	1.96	2.65
Victoria	South Eastern Melbourne, Mornington	3.97	1.82	2.56

Table 6: **Percentage of 15-64 LF immigrants from India by year of arrival and top 10 location destinations (for new immigrants)**

State	Statistical region	New immigrants	Established immigrants	Total
New South Wales	Central Western Sydney	12.44	6.31	9.00
Victoria	Inner Eastern Melbourne	11.46	6.12	8.47
New South Wales	Outer South Western Sydney	6.83	4.40	5.47
Victoria	South Eastern Melbourne, Mornington	6.34	9.75	8.25
Victoria	Outer Western Melbourne	5.12	4.59	4.82
New South Wales	North Western Sydney	4.63	8.03	6.54
Victoria	North Eastern Melbourne	4.63	2.29	3.32
New South Wales	Inner Sydney, Eastern Suburbs	3.66	2.29	2.89
Victoria	Inner Melbourne	3.41	1.53	2.36
Victoria	Southern Melbourne	3.17	2.68	2.89

Table 7: **Percentage of 15-64 LF immigrants from the Philippines by year of arrival and top 10 location destinations (for new immigrants)**

State	Statistical region	New immigrants	Established immigrants	Total
New South Wales	North Western Sydney	16.96	15.72	15.90
Victoria	Outer Western Melbourne	8.93	9.09	9.07
New South Wales	Central Western Sydney	8.04	4.62	5.12
New South Wales	Lower Northern Sydney, Northern Beaches	7.14	2.93	3.55
Western Australia	Lower Western WA	4.46	0.46	1.05
New South Wales	Inner Sydney, Eastern Suburbs	3.57	5.86	5.52
New South Wales	Canterbury-Bankstown	3.57	3.24	3.29
New South Wales	Outer South Western Sydney	3.57	6.47	6.04
Queensland	Brisbane City Outer Ring	3.57	3.08	3.15
Western Australia	Central Metropolitan (Perth)	3.57	1.08	1.45

Table 8: **Percentage of 15-64 LF immigrants from the UK by year of arrival and top 10 location destinations (for new immigrants)**

State	Statistical region	New immigrants	Established immigrants	Total
New South Wales	Inner Sydney, Eastern Suburbs	10.44	3.23	4.08
Western Australia	North Metropolitan (Perth)	10.44	5.69	6.25
New South Wales	Lower Northern Sydney, Northern Beaches	7.91	3.14	3.71
Queensland	Brisbane City Inner Ring	4.91	1.98	2.32
Victoria	Inner Melbourne	4.27	1.51	1.84
Western Australia	South West Metropolitan (Perth)	4.11	3.59	3.65
Queensland	Brisbane City Outer Ring	3.48	2.63	2.73
Queensland	North and West BDS Balance	3.16	2.51	2.58
Queensland	South and East Moreton	3.01	2.59	2.64
Western Australia	South East Metropolitan (Perth)	3.01	3.91	3.80

Table 9: **Percentage of 15-64 immigrants in the labor force by gender and time of arrival**

Ethnic group/ Gender	**New immigrants** *Male*	*Female*	**Established immigrants** *Male*	*Female*
China	48.15	51.85	53.43	46.57
India	66.34	33.66	58.32	41.68
Philippines	48.21	51.79	40.52	59.48
UK	58.86	41.14	55.99	44.01

Table 10: **Percentage of 15-64 immigrants in the labor force by age and time of arrival**

Ethnic group/	**New immigrants**				**Established immigrants**			
Age	*China*	*India*	*Philippines*	*UK*	*China*	*India*	*Philippines*	*UK*
15-19	3.44	4.15	7.14	4.43	2.94	1.91	3.54	1.08
20-24	21.96	20	9.82	4.27	8.67	4.97	11.71	2.46
25-29	26.98	31.46	12.5	15.51	6.15	9.37	9.55	3.31
30-34	17.72	22.2	16.96	21.2	6.15	8.8	12.79	5.84
35-39	15.61	10.49	22.32	20.09	11.19	15.49	8.17	11.36
40-44	8.2	4.88	17.86	17.72	20.14	15.87	15.56	18.71
45-49	2.38	3.17	8.04	8.54	18.46	14.91	13.41	16.65
50-54	2.65	2.2	4.46	4.27	14.27	11.85	14.02	14.32
55-59	0.79	1.46	0.89	2.85	7.97	10.13	9.4	16.53
60-64	0.26	0	0	1.11	4.06	6.69	1.85	9.73

Table 11: **Percentage of 15-64 immigrants in the labor force by education and time of arrival**

Ethnic group /	**New immigrants**			**Established immigrants**		
education	*12 or above*	*11 or equivalent*	*10 or below*	*12 or above*	*11 or equivalent*	*10 or below*
China	90.46	2.45	7.08	83.02	3.02	13.96
India	93.27	0.75	5.99	84.13	4.37	11.51
Philippines	79.63	2.78	17.59	82.6	3.58	13.82
UK	80.00	9.84	10.16	51.91	12.94	35.15

Table 12: **Percentage of 15-64 immigrants in the labor force by self-reported English proficiency and time of arrival**

Ethnic group /	**New immigrants**			**Established immigrants**		
English ability	*V.well/well*	*N.well/N.well at all*	*Not appl*	*V.well/well*	*N.well/N.well at all*	*Not appl*
China	73.74	23.61	2.65	70.13	26.09	3.79
India	85.89	1.73	12.38	51.25	0.96	47.78
Philippines	79.44	3.74	16.82	71.59	0.47	27.94
UK	2.54	0.00	97.46	0.98	0.06	98.96

Table 13: **Employment rate of 15-64 immigrants by gender and time of arrival**

Ethnic group /	**New immigrants**			**Established immigrants**		
Gender	*Male*	*Female*	*Total*	*Male*	*Female*	*Total*
China	0.85	0.77	0.80	0.95	0.93	0.94
India	0.88	0.8	0.85	0.97	0.99	0.98
Philippines	0.96	0.88	0.92	0.95	0.95	0.95
UK	0.95	0.93	0.94	0.96	0.97	0.96

Table 14: **Employment rate of 15-64 immigrants by education level and time of arrival**

Ethnic group /	**New immigrants**			**Established immigrants**		
education	*12 or above*	*11 or equivalent*	*10 or below*	*12 or above*	*11 or equivalent*	*10 or below*
China	0.82	0.78	0.69	0.94	0.9	0.94
India	0.85	1.00	0.79	0.99	1.00	0.90
Philippines	0.97	0.67	0.74	0.95	0.91	0.92
UK	0.95	0.85	0.98	0.98	0.94	0.95

Table 15: **Weekly income (AUD) of 15-64 immigrants by gender and time of arrival**

Ethnic group / *Gender*	**New immigrants** *Male*	*Female*	*Total*	**Established immigrants** *Male*	*Female*	*Total*
China	527.5	381.1	451.5	715.7	621.1	672
India	690.8	587.6	656.1	1116.9	866.7	1013
Philippines	806.6	575.4	685.8	827.5	715.8	761
UK	1159.8	809.2	1014.9	1109.5	746.7	949.4

Table 16: **Weekly income (AUD) of 15-64 immigrants by education level and time of arrival**

Ethnic group / education	**New immigrants** *12 or above*	*11 or equivalent*	*10 or below*	**Established immigrants** *12 or above*	*11 or equivalent*	*10 or below*
China	461.5	330.6	306.8	708.2	666.3	461.6
India	654.4	1258.3	629.2	1070.7	543.2	793.8
Philippines	757.4	366.7	476.3	803.8	544.3	607.1
UK	1093.5	635.2	800.8	1081.9	848.9	800.6

Table 17: **Employment regression results**

Dependent variable/ Independent vars	1 dprobit Empl rate	2 OLS Empl rate	3 IV Empl rate	4 OLS Empl rate	5 IV Empl rate	6 OLS Empl rate	7 IV Empl rate
thnd of employed old imm	0.451	0.355	0.417	0.338	0.358		
from country j in area r	(3.56)**	(3.09)**	(3.94)**	(2.09)*	(1.95)*		
employment rate				2.733	2.568	-1.065	-1.136
in state S				(0.65)	(0.58)	(0.89)	(0.21)
India x thnd of est Indian						-0.313	-1.022
imm in area r						(0.48)	(1.23)
China x thnd of est Chinese						-0.603	-1.217
imm in area r						(2.05)*	(2.29)*
Philip x thnd of est Philip						0.704	0.418
imm in area r						(1.28)	(0.65)
UK x thnd of est UK						0.426	0.305
imm in area r						(3.92)**	(1.76)
male dummy	0.053	0.055	0.055	0.054	0.054	0.053	0.051
	(3.28)**	(3.35)**	(3.35)**	(3.21)**	(3.21)**	(3.21)**	(3.10)**
married dummy	-0.008	-0.011	-0.011	-0.011	-0.011	-0.005	-0.002
	(0.42)	(0.55)	(0.55)	(0.55)	(0.54)	(0.23)	(0.08)
Highest edu: grade 11	-0.095	-0.069	-0.07	-0.077	-0.078	-0.078	-0.078
	(2.18)*	(1.79)	(1.82)	(1.92)	(1.94)	(2.03)*	(1.94)
Highest edu: grade 10	-0.037	-0.04	-0.039	-0.038	-0.038	-0.039	-0.037
and below	(1.35)	(1.51)	(1.46)	(1.42)	(1.43)	(1.49)	(1.39)
age	0.011	0.014	0.014	0.015	0.015	0.012	0.012
	(1.9)	(2.38)*	(2.40)*	(2.47)*	(2.43)*	(2.12)*	(2.00)*
age squared	0	0	0	0	0	0	0
	(1.44)	(1.91)	(1.93)	(2.01)*	(1.98)*	(1.73)	(1.65)
State dummies	Yes	Yes	Yes	No	No	No	No
Constant		0.55	0.429	-2.054	-1.896	1.598	1.689
		(5.45)**	(0.4)	(0.51)	(0.45)	(1.4)	(0.33)
Observations	1513	1532	1532	1532	1532	1532	1532
R-squared		0.04		0.03		0.05	

Note: Absolute value of t-stat in parentheses; * significant at 5 percent, ** significant at 1 percent; omitted category of educational level - grade 12 and above

Note: t-stats are calculated using unclustered standard errors. We also estimated model with clustered standard errors, but it had no impact on the results

Table 18: **Income regression results**

	1	2	3	4
Dependent variable/	OLS	IV	OLS	IV
Independent vars	Weekly income	Weekly income	Weekly income	Weekly income
mean income of est imm	1.037	1.355	1.047	1.344
from country j in area r	(15.39)**	(13.01)**	(16.31)**	(13.33)**
Employment rate			-164.867	2401.23
in state S			(0.08)	(0.45)
male dummy	242.157	237.37	242.727	236.501
	(7.63)**	(7.40)**	(7.67)**	(7.28)**
married dummy	26.028	63.721	26.033	62.159
	(0.69)	(1.61)	(0.69)	(1.58)
Highest edu: grade 11	-238.224	-259.354	-240.585	-271.662
	(3.63)**	(3.93)**	(3.68)**	(3.84)**
Highest edu: grade 10	-158.607	-154.789	-156.557	-157.334
and below	(3.16)**	(3.07)**	(3.14)**	(3.14)**
age	78.709	70.762	77.634	70.034
	(7.16)**	(6.24)**	(7.12)**	(6.23)**
age squared	-0.905	-0.822	-0.891	-0.813
	(6.22)**	(5.52)**	(6.16)**	(5.49)**
State variables	Yes	Yes	No	No
Constant	-1765.75	-1912.77	-1601.91	-4145.82
	(9.25)**	(9.82)**	(0.85)	(0.81)
Observations	1107	1093	1107	1093
R-squared	0.35		0.35	

Note: Absolute value of t-stat in parentheses; *significant at 5 percent, ** significant at 1 percent; omitted category of educational level - grade 12 and above

Note: t-stats are calculated using unclustered standard errors. We also estimated model with clustered standard errors, but it had no impact on the results

Table 19: **Income regression results**

	5	6	7	8
Dependent variable/	OLS	IV	OLS	IV
Independent vars	Weekly income	Weekly income	Weekly income	Weekly income
Employment rate			-3515.25	8383.787
in state S			(1.71)	(0.65)
China x mean income of Chinese	0.353	1.758	0.485	1.795
est imm in stat region r	(2.67)**	(2.59)**	(4.06)**	(2.22)*
Philippines x mean income of	0.545	1.755	0.663	1.768
Filipino est imm in stat region r	(4.26)**	(3.08)**	(5.68)**	(2.68)**
UK x mean income of British	0.755	1.569	0.833	1.577
est imm in stat region r	(9.26)**	(4.03)**	(11.23)**	(3.53)**
male dummy	235.692	240.221	237.657	235.503
	(7.53)**	(7.35)**	(7.60)**	(6.96)**
married dummy	41.116	65.545	38.408	65.627
	(1.1)	(1.59)	(1.03)	(1.55)
Highest edu: grade 11	-277.458	-245.606	-279.34	-269.761
	(4.27)**	(3.58)**	(4.30)**	(3.74)**
Highest edu: grade 10	-184.528	-146.948	-173.502	-152.145
and below	(3.71)**	(2.68)**	(3.51)**	(2.83)**
age	75.705	69.89	74.31	69.868
	(6.99)**	(5.95)**	(6.89)**	(6.06)**
age squared	-0.89	-0.806	-0.872	-0.807
	(6.20)**	(5.17)**	(6.11)**	(5.28)**
State variables	Yes	Yes	No	No
Constant	-1281.29	-2182.44	1936.792	-10084.4
	(6.26)**	(4.68)**	(0.98)	(0.8)
Observations	1107	1093	1107	1093
R-squared	0.37		0.37	

Note: Absolute value of t-stat in parentheses; *significant at 5 percent, ** significant at 1 percent; omitted category of educational level - grade 12 and above

Note: t-stats are calculated using unclustered standard errors. We also estimated model with clustered standard errors, but it had no impact on the results

Table 20: **Income regression results**

Dependent variable/ Independent vars	1 OLS Weekly income	2 IV Weekly income	3 OLS Weekly income	4 IV Weekly income
thnd of employed old immigrants	1739	2370	1751	2315
from country j in area r	(7.45)**	(9.28)**	(8.05)**	(6.53)**
Employment rate in state S			-9046	-13642
			(3.92)**	(1.88)
male dummy	264	261	265	263
	(7.75)**	(7.62)**	(7.73)**	(7.61)**
married dummy	-80	-73	-87	-82
	(1.99)*	(1.82)	(2.17)*	(2.03)*
Highest edu: grade 11	-217	-240	-229	-241
	(3.06)**	(3.37)**	(3.23)**	(3.27)**
Highest edu: grade 10	-193	-197	-186	-194
and below	(3.57)**	(3.63)**	(3.44)**	(3.57)**
age	98	94	98	93
	(8.40)**	(8.00)**	(8.33)**	(7.72)**
age squared	-1	-1	-1	-1
	(7.22)**	(6.91)**	(7.15)**	(6.62)**
State variables	Yes	Yes	No	No
Constant	-1,335	-1,316	7,166	11,543
	(6.55)**	(6.43)**	(3.26)**	(1.67)
Observations	1107	1107	1107	1107
R-squared	0.25		0.24	

Note: Absolute value of t-stat in parentheses; *significant at 5 percent, ** significant at 1 percent; omitted category of educational level - grade 12 and above

Note: t-stats are calculated using unclustered standard errors. We also estimated model with clustered standard errors, but it had no impact on the results

Table 21: **Income regression results**

	5	6	7	8
Dependent variable/	OLS	IV	OLS	IV
Independent vars	Weekly income	Weekly income	Weekly income	Weekly income
Employment rate in state S			-15759	-30995
			(6.74)**	(3.62)**
China x thnd of est	-3899	-4433	-2976	-4485
Chinese imm in area r	(6.83)**	(4.84)**	(5.53)**	(4.90)**
Philip x thnd of est Philip	-1422	-1951	-288	-1597
imm in area r	(1.44)	(1.78)	(0.3)	(1.43)
UK x thnd of est UK	1531	1434	1717	1926
imm in area r	(6.84)**	(5.33)**	(8.20)**	(5.88)**
male dummy	249	248	254	257
	(7.66)**	(7.62)**	(7.70)**	(7.63)**
married dummy	-18	-14	-40	-19
	(0.48)	(0.35)	(1.03)	(0.46)
Highest edu: grade 11	-259	-260	-273	-242
	(3.83)**	(3.84)**	(3.99)**	(3.36)**
Highest edu: grade 10	-203	-202	-188	-190
and below	(3.94)**	(3.93)**	(3.61)**	(3.57)**
age	86	85	86	78
	(7.63)**	(7.57)**	(7.59)**	(6.40)**
age squared	-1	-1	-1	-1
	(6.65)**	(6.59)**	(6.62)**	(5.54)**
State variables	Yes	Yes	No	No
Constant	-862	-824	13,858	28,441
	(4.33)**	(4.03)**	(6.18)**	(3.48)**
Observations	1107	1107	1107	1107
R-squared	0.32		0.3	

Note: Absolute value of t-stat in parentheses; *significant at 5 percent, ** significant at 1 percent; omitted category of educational level - grade 12 and above

Note: t-stats are calculated using unclustered standard errors. We also estimated model with clustered standard errors, but it had no impact on the results

A Appendix

A.1 Derivation of $\frac{\partial x^*(n)}{\partial n}$ and $\frac{\partial w^*(n)}{\partial n}$

We know that in equilibrium a vector of unemployment values $U^* = (U^*_E, U^*_{NE})$ solves

$$rU_J = b + \frac{\lambda(n)}{r+\delta}[p\int_{rU_J+d(n)I(w,p)}(x - d(n)I(w,p) - rU_J)dG(x) + \\ +(1-p)\int_{rU_J}(x - rU_J)dG(x)] \tag{15}$$

given a vector of $(\lambda, n, \eta, \rho, b, \alpha, d, p)$ and $cdf\,G(x)$.

What would be $\frac{\partial x^*(d,p,n)}{\partial n}$?

Define $\rho U_{NE} \equiv x^*(d,p,n)$ for $0 < p < 1$ and $d > 0$; and $\rho U_E \equiv x^*(0,0,n)$. Use the result of integration by parts that $\int_{x^*}(x - x^*)dG(x) = \int_{x^*}(1 - G(x))dx = \int_{x^*}\tilde{G}(x))dx$ where $(1 - G(x)) \equiv \tilde{G}(x))$. Then re-write equation (15) as

$$x^*(n) = b + \frac{\lambda(n)}{\rho+\eta}\Big[p\int_{x^*(n)+d(n)}\tilde{G}(x)dx + (1-p)\int_{x^*(n)}\tilde{G}(x)dx\Big] \tag{16}$$

Take a derivative of $x^*(n)$ wrt n

$$\frac{\partial x^*(n)}{\partial n} = \frac{\partial\lambda(n)}{\partial n}\frac{1}{\rho+\eta}\Big[p\int_{x^*(n)+d(n)}\tilde{G}(x)dx + (1-p)\int_{x^*(n)}\tilde{G}(x)dx\Big] - \\ -\frac{\lambda(n)}{\rho+\eta}\Big[\Big(\frac{\partial x^*(n)}{\partial n} + \frac{\partial d(n)}{\partial n}\Big)p\tilde{G}\big(x^*(n)+d(n)\big) + \\ +\frac{\partial x^*(n)}{\partial n}(1-p)\tilde{G}\big(x^*(n)\big)\Big] \tag{17}$$

Re-arrage and get

$$\frac{\partial x^*(n)}{\partial n} = \frac{\frac{\partial\lambda(n)}{\partial n}\frac{1}{\rho+\eta}\Big[p\int_{x^*(n)+d(n)}\tilde{G}(x)dx + (1-p)\int_{x^*(n)}\tilde{G}(x)dx\Big] - \frac{\lambda(n)}{\rho+\eta}\frac{\partial d(n)}{\partial n}\tilde{G}\big(x^*(n)+d(n)\big)}{1 + \frac{\lambda(n)}{\rho+\eta}\Big[p\tilde{G}\big(x^*(n)+d(n)\big) + (1-p)\tilde{G}\big(x^*(n)\big)\Big]} \tag{18}$$

The denominator of this expression is positive. The sign of numerator depends on parameters' values.

First, notice that if we are considering the case of English speaking migrants, then numerator is positive too. In other words, for English speakers $\frac{\partial x^*(n)}{\partial n} > 0$. For non-English speakers we can have either positive or negative impact of network on the equilibrium productivity.

What about equilibrium reservation wages? From worker equilibrium condition we know that $w_j^* = \rho U_j$.

From Nash bargaining result at the equilibrium we know that for English speakers and non-English speakers who face non-sensitive employers $w^* = x^* = \rho U$

On the other hand, for non-Enligh speakers who face sensitive employers

$w^* = \rho U$ and $x^* = \rho U + d(n)$ or $x^* = w^* + d(n)$. Thus, $w^* = x^* - d(n)$

Therefore, for English speakers and non-English speakers who face non-sensitive employers $\frac{\partial w^*(n)}{\partial n} > 0$.

However, for non-English speakers who face sensitive employers $\frac{\partial w^*(n)}{\partial n}$ can be negative, since $\frac{\partial w^*(n)}{\partial n} = \frac{\partial x^*(n)}{\partial n} - \frac{\partial d(n)}{\partial n}$.