Economic Network Effects and Immigrant Earnings

Abstract

Do ethnic enclaves assist or hinder immigrants' economic performance? The empirical literature on this question is inconclusive. In this paper, we extend the literature by constructing a dynamic variable from micro-panel data to capture the effects of spatial networks of immigrants' ethnic-specific resources. We account for endogeneity of the network and other variables. Using the HILDA data set, and a suite of robustness checks, results show that immigrants' earnings are positively associated with the concentration and resources of their country-of-birth group. The effect is prominent for immigrants born in non-English-speaking countries and for high-skilled immigrants, highlighting positive ethnic network spill-over effects for these groups. Moreover, accounting for the network variable provides a viable explanation for the divided previous international results on ethnic concentration.

Keywords: immigrant earnings; network spill-over effects; ethnic concentration; longitudinal; Hausman-Taylor

Classification codes: J30, J31, Z13, Z18.

I Introduction

With increased international mobility in recent decades, the economic performance of immigrants is an increasingly important indicator of how immigrant groups perform in a host country. Given the potential link between earnings and productivity, the labour market performance of immigrants is of interest across immigrant-receiving countries. This question is especially relevant to an increasing number of countries in which immigrants comprise a significant proportion of their population. For example, according to the 2016 Australian Census of Population, 28.5 percent of the residents living in Australia were foreign-born (Australian Bureau of Statistics 2017).

This paper is at the intersection of two major streams of research: the labour market analysis of immigrant earnings, and the recent literature that incorporates the impacts and co-dependence of outcomes resulting from spatial networks. In our analysis, we contribute to the literature by formally exploring the impact of the economic resources of immigrant ethnic groups on immigrant earnings, and we address co-dependence and potential endogeneity in the models.

It is well recognised in the economics literature that, in contrast to natives, immigrants are potentially at a disadvantage in the host country's labour market, as they may typically lack social networks, information about job opportunities, language fluency, and firm-specific training (e.g., Borjas 1995; Chiswick 1978; Cobb-Clark 2003). In addition, it is empirically verified that the average earnings of different immigrant ethnic groups have diverse patterns by ethnic group (e.g., Beenstock et al. 2010; Borjas 1992).

It is also observed that, across immigrant-receiving countries, a mechanism immigrants may use to mitigate some of these difficulties is geographic co-location. Specifically, geographic concentration and the establishment of shared markets and networks based on ethnicity or other shared characteristics could increase opportunities that result in higher earnings. This positive effect is supported by studies such as, for example, Edin et al. (2003), Portes and Shafer (2007), Reitz (2007), and Piracha et al. (2016).

However, the international evidence provides contrasting results on whether ethnic concentration by itself leads to positive or negative outcomes for immigrants. For example, in contrast to studies that show positive effects, Aldrich et al. (1987) find mixed results from ethnic concentration. Chiswick and Miller (2002) and Bertrand et al. (2000) show that ethnic concentration negatively influenced immigrants' labour market performance due to limited opportunities (with U.S. data). Similarly, Clark and Drinkwater (2000) find negative results, attributing this to smaller markets and saturation of economic opportunities (with U.K. data). These studies are compatible with a possible ghetto effect from geographic concentration of ethnic minorities.

These findings raise interesting questions about whether or not geographic concentration based on country of origin or cultural background can influence immigrants' labour market performance. In particular, whether the co-dependence of earnings outcomes of immigrants affects their earnings is a less-studied question that we incorporate into our analysis.

Most economic studies have adopted ethnic concentration/enclave as the proxy for networks of immigrants in the host country (e.g., Edin et al. 2003). Other studies have used language group (e.g., Bertrand et al. 2000; Chiswick and Miller 2002). Recent studies have increasingly noted the need for analyses that recognise that immigrants are potentially connected with immigrants from their own ethnic or country-of-origin group. This effect is distinct from what can be captured through conventional ethnic concentration ratios, such as size of the network, information, and job referrals (Battu et al. 2011; Piracha et al. 2016).

A second stream of recent studies has focused more formally on the geographic network effects of immigrant enclaves on some economic outcomes (e.g., Baltagi et al. 2014; Baltagi et al. 2017; Battu et al. 2011). In particular, studies that incorporate spatial economic factors have received recent attention across economic and social dimensions. This approach lends itself to extensions of modelling immigrant earnings and related integration/assimilation studies (e.g., Adjemian et al. 2010; Baltagi 2013; Baltagi and Liu 2011; Goetzke 2008; Goetzke and Weinberger 2012; Wang and Maani 2014).

In particular, we address two main questions:

- Is ethnic geographic concentration positively or negatively associated with the economic performance of immigrants, and, especially, what is the role of ethnic-group economic resources?
- Is there a difference in such associations for immigrants by skill and country of origin (English- or non-English-speaking)?

We examine these questions using a rich longitudinal (panel) data set to integrate the impact of networks of economic resources for immigrant groups within a panel setting.

The contributions of this paper to the literature are as follows. First, in our analysis, we extend the earnings model to incorporate spill-over effects resulting from networks of economic resources through geographic co-location. Specifically, we construct a spatial network variable measure to represent the individual immigrant's network of economic resources (ethnic capital), based on geographic location, country of origin (birth), and survey year from individual level data within a panel setting.[1] This approach enables us to incorporate the correlation of immigrants' integration outcomes, with the goal of obtaining a more accurate estimation of the key variable of ethnic concentration effects. The approach also provides a modelling mechanism to incorporate seemingly contrasting positive and negative effects of immigrant ethnic concentration when networks of economic resources are absent from the model.

Second, endogeneity due to unobservables is of special relevance in capturing the effects of network and ethnic concentration variables. We address potential endogeneity issues relating to the network variable, ethnic concentration, and other variables within the earnings model by using the panel features of the data set, in combining the spatial lag structure with IV estimation within the Hausman-Taylor (HT) model specification for labour market outcomes of immigrant earnings (Baltagi 2013; Baltagi and Liu 2011).

We show that the HT model, augmented by the spatial ethnic network effect, is econometrically identified (see *Technical Note* (Supplementary Appendix) and, for example, Baltagi et al. (2014) on the specification and identification of the Hausman-Taylor model with a spatial lag component). We use a suite of robustness checks, which validate the model selected, and we report on base models using OLS, fixed effects (FE), and random effects (RE) estimations and selection tests. We further provide comparative robustness tests across General Method of Moments (GMM) results, which confirm the reported HT results.

Third, the analysis validates results in an improved modelling framework on the effect of ethnic network outcomes for immigrants from four major sub-groups of English-speaking and non-English-speaking backgrounds, and for high-skilled and less-skilled immigrants.

We test our model in Australia, traditionally a country of immigrants where the integration of immigrants influences the country's economy and society. In addition, the modelling approach and findings can be applied to studies for other countries.

The paper is arranged as follows. Section two provides a brief discussion on immigrant networks in the relevant literature. In Section three we discuss the data set employed. In Section four we discuss the network variable and the estimation approaches adopted in this study. We also show that the first-order spatial network variable adopted is identified in the Hausman-Taylor setting under reasonable conditions that can be generally easily met (Lee 2007) in Section five. Section five further provides information on the variable selection. Empirical results and robustness checks are discussed in Section six. Section seven concludes this paper.

II Immigrant Earnings and Country-of-Origin Economic Networks

Individuals are inherently linked through the groups (e.g., ethnicity) they belong to. These groups include friendships, kinship, shared history, and other relationships. Life in a common environment produces shared experiences, knowledge, information, and other products mediated by these kinds of networks.

A group of studies show that social and economic networks can exert a significant influence on labour market performance of a group. Among economics studies, the theory of 'ethnic capital' was among the earliest studies that hypothesised that the economic outcomes of immigrants' children are likely to be influenced by their parental resources (e.g., Borjas 1992). Battu et al. (2011) observed that ethnicity increases the probability of networks being used. Thus, the labour market performance of an individual is potentially correlated with that of other individuals from their spatial and social/ethnic network. We address this co-dependence in the analysis of immigrant earnings.

Conceptually, immigrants may find greater opportunities for employment by residing in the same geographic area. Ethnic concentration effects, for example, can occur for several reasons. First, geographic co-location creates job opportunities for immigrants in ethnic-specific markets (Fong and Shen 2011). Specifically, immigrant-owned businesses can provide added employment opportunities by lowering the requirements for employment, such as being skilled in the local language or having a recognised qualification. In many cities, immigrant markets can provide the main source of employment and earning opportunities for immigrants who come from the same country-of-birth group (e.g., Portes and Shafer 2007). Second, the immigrant market is potentially important for local businesses. Because native-born employees might know little about the immigrants' culture and language, mainstream employers might prefer to hire immigrants to serve the target immigrant market, generating more jobs by ethnic and geographic concentration (e.g., Edin et al. 2003).

However, by lowering employment barriers for immigrants, an ethnic enclave reduces the bargaining power of immigrants, since over time it can make employment outside of the ethnic enclave less achievable (e.g., working in an ethnic enclave can reduce the benefit associated with learning English). Some international studies have indicated negative effects of ethnic concentration on immigrants' earnings. For example, Chiswick and Miller (1996, 2002) and Bertrand et al. (2000) showed that linguistic concentration negatively influenced immigrants' labour market performance in the United States. Warman (2007) found similar results for Canada. In contrast, Edin et al. (2003) found that immigrants' earnings were positively correlated with ethnic concentration in some cases in Sweden, when adjusting for endogeneity of ethnic capital.

As a result, the effect of ethnic networks on immigrants' earnings is *a priori* unknown by country-of-origin language group or locality depending on the strength of such resources.

While most of the earlier literature relied on ethnic concentration ratios to measure these effects, another important factor – the economic strength of the groups' network of resources – has not received adequate attention. It is common for economic resources to differ significantly across immigrant ethnic groups and across cities in the host country. The omission of this variable may explain the contrasting results in the literature, since both positive and/or negative omitted effects of group economic resources were attributed to ethnic concentration. An example is the case of large geographic ethnic concentrations of one or more low-income immigrant ethnic groups, accompanied by a ghetto effect due to low resources. Geographic concentration could result from historic, geographic, or cost constraints, among other reasons. In this case, and compared to smaller concentrations of higher resourced ethnic groups, the omitted low or negative spill-over effects would be added and attributed to ethnic concentration.

III Data

Immigration has a long history in Australia, and her multi-cultural immigration policy since the 1970s has created a diverse and vibrant population from several countries of origin. Major cities, such as Sydney, Melbourne, Brisbane, Perth, Adelaide, and Canberra (ACT), have concentrations of ethnic populations and a work force composed of a variety of ethnic groups. Concentrations of immigrant groups and their economic resources also differ significantly by ethnicity and location. This feature of Australian data is of special interest for this research, and we incorporate it into our study of immigrant earnings outcomes.

(i) The Household, Income, and Labour Dynamics in Australia (HILDA) Survey

The HILDA survey is a major Australian longitudinal data set administered by the Australian Government, in collaboration with the University of Melbourne. The survey is similar in design and coverage to the British Household Panel Survey and the Panel Survey of Income Dynamics in the U.S. The HILDA panel data set contains dynamic information about earnings, education, country of origin, residence location, decade of arrival in the host country, and family of surveyed individuals, for both Australian natives and immigrants. In addition, HILDA includes information of the city of residence in major Australian metropolitan areas, considered in our analyses. This approach is a continuation of a majority of earlier studies that have examined immigrants' geographical decisions in the light of Standard Metropolitan Statistical Areas (SMSAs).

The initial HILDA survey in 2001 included 7,682 households and 19,914 individuals in a nationally representative survey. This original HILDA survey was a representative sample of the overall Australian labour force in 2001. In addition, annual longitudinal sample weights provided by the HILDA survey maintain the representation of the original sample over time. Our analysis follows this population group for nine further consecutive years (2002 to 2010). Our choice of data years is guided by the HILDA survey. With some major changes in HILDA data in 2011, the years selected gives us a period of continuous data and consistent group inclusion in the data. Observations of full-time employed male immigrants, aged between 25[2] and 64 years, created a merged unbalanced panel longitudinal data set that contains 2,936 observations. This final data set, including data on all required variables, was used for the regressions.

A major advantage of the HILDA data set is that it allows the use of appropriate panel data techniques based on longitudinal information with rich coverage of relevant variables. These factors allow controls for endogeneity and unobserved individual heterogeneity, which are particularly important in the analyses of earnings and network effects. As an example to illustrate the nature of the data used, Australian immigrants who are born in China, Vietnam, Greece, Canada, and New Zealand, and who were living in Melbourne in the first survey, had different average earnings. Immigrants born in these countries also resided in Sydney, Brisbane, and other major metropolitan areas in the original survey, providing comparative data. Each country-of-birth group also experienced variations in earnings changes from year to year and across cities, beyond city and time fixed effects. This characteristic of the data provides relevant data variation for the analysis.

A second advantage of this data set is that it allows a significant duration for the analysis. During the ten-year time period, the individuals experienced changes in their personal and geographic group earnings and we are able to track that in our analysis. In addition, 5 percent of immigrants in our data had changed their metropolitan area at least once during the course of the study, providing further useful data variation.

A limitation of the data set is that it mainly covers immigrants who were present in Australia in 2001, with small additions to the sample over the next data periods. Therefore, the analysis does not cover most new immigrants since 2001. However, we believe that given the objectives of the study, the advantages of the data set outweigh this particular limitation.

Considering issues of attrition and selection, the HILDA data set applied in this research has a remarkably high response rate throughout the period of the analysis (e.g., 96.3 percent in wave 10 (Watson 2010)). In all of our models, we take further precautionary measures by applying the longitudinal weights of the HILDA data set, designed to account for attrition, and the alignment of data with the representative population sample in the base year of the survey. As we discuss in Section VI on robustness, auxiliary sample-selection models (Heckman 1979) show that the results in general, and in particular the results of interest on the ethnic economic network, and the ethnic concentration variables, were not sensitive to the sample selection adjustments.

In our sample, immigrants came from 67 countries (each country contributed an average of 44 observations). The size of country-of-birth groups in each major city has a wide range, including some small cells for countries with few immigrants to Australia. However, this is econometrically desirable because it provides a wide range of geographic ethnic concentration ratios, as derived from related Census data years. In addition, the weighted construction design of the network variable incorporates the size of the country-of-birth group in each city in the survey.

Immigrants from different countries of origin historically show different earnings trajectories and different reliance on geographic concentration.

In addition to our main analyses, we report results based on a division of our data into two major pooled subsample groups based on language: from the main English-speaking countries (ESC)[3] and non-English-speaking countries (NESC). We also provide results for pooled separate subsample groups of high-skilled and less-skilled immigrants. We report on a suite of auxiliary goodness of fit and robustness checks.

Table 1 represents the socio-economic characteristics of full-time employed immigrant males, aged between 25 and 64 years. Table 1, for example, shows higher ethnic geographic concentration rates and lower mean hourly earnings for immigrants from non-English-speaking countries relative to English-speaking country of origin, and high-skilled and less-skilled groups. In our analysis, we examine the impact of such concentrations on earnings in models that control for human capital and other relevant variables.

[Table 1 here]

(ii) Variables

The dependent variable in the model is the natural logarithm of the real hourly wage for each individual observation across time. The main explanatory variable (Wy) represents the immigrant group's geographic and economic network effect. We derive Wy from HILDA at the individual level, incorporating longitudinal, country-of-birth, and location dimensions. We detail the relevant literature and the derivation of the network variable in Section IV.

The other variables incorporate ethnic concentration and the conventional human capital model specifications, and they are also derived from HILDA. These include potential years of work experience, higher-education qualifications, and marital status, in addition to the cohort of arrival and city and time fixed effects. We also include whether the respondent was born in an English-speaking country. This variable reflects language proficiency and familiarity with the cultural setting (Chiswick and Miller 1995). We further discuss variable specifications in the discussion of our econometric model and addressing endogeneity in Section V(i).

The ethnic concentration variable is derived from the Australian Census of Population (years 1996, 2001, and 2006). It is matched for each observation based on the individual's country of origin, city of residence, and year (in lagged form).

IV Model Specifications

Our modelling approach uses panel (longitudinal) data and incorporates network spill-over effects (of order-one, referring to the immigrant's from the same ethnic and geographic group) within a Hausman and Taylor (1981) panel estimation method that addresses the potential endogeneity of the network and other variables. In our analysis, we examine both the impact of ethnic concentration among immigrants and the spill-over effects of their economic resources on their economic performance.

In our ten-year longitudinal data set, immigrants experience changes in variables of interest over time, allowing observed variations across cities, ethnic groups, and time for groups and individuals.

In Section IV(i) we discuss the economic ethnic network variable that we incorporate into our modelling approach. In Section V we discuss the specific Hausman-Taylor model that we have developed for the analysis.

(i) Network Variable

We consider the economic network of immigrants within a matrix of the network for each country-of-origin group residing in the same metropolitan area in each year. We incorporate a spatial component (a spatial lag of order-one) and adjust for potential endogeneity in the panel setting through the HT estimation method. Therefore, the model takes the form of equation (1).[4] This component of our econometric model is inspired by the second stream of research noted earlier (e.g., Goetzke 2008; LeSage and Pace 2009; Baltagi 2013; Baltagi and Liu 2011; Lee 2007).

In the econometric model, individuals who are from the same country-of-birth group and residing in the same location are first-order ethnic network members. Thus, 'ethnic-spatial dependence' represents the case that an individual's labour market performance is influenced by the labour market performances of members of their ethnic-spatial network and other ethnic capital factors in that location.

A dynamic spatial lag of order-one (e.g., network groups in the same city or province) is generally applied for socio-economic factors. Conley and Topa (2002), for example, studied spatial patterns in unemployment by analysing agents' order-one social networks. Similarly, Baltagi, Deng, and Ma (2017) examined the network effects on labour contracts of internal migrants in China by using proxies of social networks of order-one. This is in contrast to, for example, biological models where the spread of disease is likely to be affected by spatial lags of higher orders. But it is logical for socio-economic factors, where the closest network of resources tend to influence group-member outcomes most prominently.

The network matrix W is derived from a first-order ethnic-spatial-network matrix *E*. As discussed earlier, the matrix *E* in this case is constructed by: country of origin, year of survey, and location. Matrix *E* in equation (1) below provides an example. Suppose P1, P4, P5, P7, and P10 are all persons from the UK; P1, P4, and P5 are located in location A, while P7 and P10 are persons located in location B. Suppose P2, P6, and P8 are individuals from China; P2 and P6 are both located in location A, while individual P8 is located in location B. Finally, suppose P3 and P9 are from France and reside in two different areas in Australia. Thus, the 10×10 first-order ethnic-spatial network matrix *E* is, in this case:

$$E = \begin{bmatrix} & P1 & P2 & P3 & P4 & P5 & P6 & P7 & P8 & P9 & P10 \\ P1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ P2 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ P3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ P4 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ P5 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ P6 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ P7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ P8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ P9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ P10 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \qquad (1)$$

When the elements of matrix *E* are zeroes, individuals are deemed not to be first-order ethnic-spatial network members. The diagonal elements of the matrix are zeroes, which means that individuals are not considered as ethnic-spatial network members to themselves.

Since the number of an individual's first-order ethnic-spatial network members varies over time, the mean (rather than the cumulative) value of the variable over the network group observations is the appropriate measure for analysis. As a result, in order to define an 'ethnic-spatial lag', matrix *E* is normalised by rescaling each row so its elements sum to one. This yields the ethnic-spatial weight matrix *W*. The entries in matrix *W* can take the values of 0, 1, ½, ⅓, ¼, etc. depending on the number of members in the group:

We acknowledge that the terms 'ethnic concentration' or 'ethnic networks' can assume different definitions based on spoken language, race, shared culture, etc., each of which could be right given the specifics of a study. In this analysis, we define ethic groups and ethnic concentration on the basis of country of origin. While we acknowledge that it is possible for individuals born in the same country to have different races or ethnicity, this definition has a number of advantages that supersede this drawback. Notably, a shared country of birth generally comes with a shared culture, language, and history. In addition, from an econometric point of view, and compared to other self-reported measures based on factors such as ethnicity, language, or race, country of birth is more clearly an exogenous variable.

V *Econometric Model*

Among modelling approaches, the Hausman-Taylor (HT) estimator, which adopts instrumental variables (IV) estimation, controlling for endogeneity of the spatial lag variable and other endogenous explanatory variables, lends itself well to the study's objectives.

We examine and control for potential endogeneity of the network and other relevant variables, using the Hausman and Taylor (1981) panel estimation method. This is a four-step approach that combines features of instrumental variables, fixed-effects, and two-stage least squares, resulting in consistent estimators. For a comprehensive discussion of the use of the HT method for addressing endogeneity with the panel data set employed in this study, we refer the reader to Breunig et al. (2013). We provide results in Section VI based on OLS (as a base), FE, and RE estimations, and show that the HT model is the more robust estimation method in this setting. We find that these initial auxiliary results (on human capital and other conventional variables) resonate closely with previous immigrant earnings model results with the HILDA data set we employ.

One of the advantages of the HT estimation, in this case, is that it can combine greater information based on FE and RE estimations to account for endogeneity. Another major advantage of the HT estimator, in this setting, is that it allows one to examine the effect of time-invariant variables, such as English-speaking background (ESC) and cohort of arrival, which are important to migration studies (see, for example, Breuning et al. 2013). In addition, statistical tests can confirm if the HT model is at least as good as the FE model. We test and confirm that the use of the HT model in our analysis improves efficiency compared to FE (discussed in Section VI).

The HT model takes the linear form:

$$y_{it} = \rho \sum_{j \neq i} w_{ijt} y_{jt} + \sum_{h=1}^{k} x_{ith} \beta_h + \sum_{m=1}^{g} z_{im} \gamma_m + \varepsilon_{it} \qquad (2)$$

where y_{it} is (the logarithm of) earnings of individual i in period t, and w_{ijt} is a data dependent weight which reflects, in period t, the difference in ethnicity and geographic location between individuals i and j. The effects of the three sets of variables are given by the coefficients β_h, γ_m and ρ, with the last of these reflecting the direction and overall strength of the ethnic capital effects. The structure of the model, especially the nature of the ethnic-spatial autocorrelation feature, is more conveniently shown expressed in terms of matrices and vectors, so we write it as

$$y_t = \rho W_t y_t + X_t\beta + Z\gamma + \varepsilon_t,\ t = 1,\ldots,T \quad (3)$$

where y_t is a $n \times 1$ vector of observations on n individuals for period t (the model is a panel data model in the sense that the same individuals are observed over the T periods). $W_t y_t$ reflects labour market performances of an individual's ethnic-spatial network members. X_t is a $n \times k$ matrix of observations on time-varying covariates for period t, and Z is a matrix of observations on time-invariant characteristics.

The other components on the right-hand side of (2) and (3) have essentially a Hausman and Taylor (1981) panel data structure. In (2) and (3) the components of Z are observed and time invariant, while those of X_t are observed and time varying, and ε_t also consists of an unobserved time-invariant component, α, and a conventional disturbance component, η_t, i.e., $\varepsilon_t = \alpha + \eta_t$. In the HT model, dependence between some columns of X_t and α is allowed, as is dependence between some columns of Z and α. X_t includes socio-economic and personal characteristics of individuals (e.g., education level, and years of experience). The unknown coefficients are the scalar ρ and the vectors β and γ.

The incorporation of the spatial component adds an additional variable ($W_t y_t$), along with an additional unknown coefficient, to the HT set-up, and is intended to capture the immigrant network and ethnic capital effects discussed in the previous section.[5] We treat $W_t y_t$, along with other relevant variables as endogenous and time varying.[6]

A fuller discussion of the exact HT specification, identification and estimation of the model is contained in Section V(i) and the *Technical Note* in the Supplementary Appendix. These assumptions, which are comfortably met in our analysis, are that the number of exogenous time-varying variables X_{1t} (e.g., year fixed effects) in the HT model (k_1), is greater than (or equal to) the number of the endogenous time-invariant variables, Z_2, in the model (g_2) plus one (i.e., $k_1 \geq g_2 + 1$). In addition, regarding the spatial lag variable, the diagonal elements of the matrix must be zeros, indicating that the individual is excluded from the group means. Finally, as Lee (2007) shows, variation in group sizes in addition to the assumptions above can yield identification for the spatial lag variable. These assumptions are met in our analysis.[7]

(i) Accounting for Endogeneity and Variable Specifications

The longitudinal nature of the data, and panel data estimation, allows us to observe changes in individual earnings as immigrants experience different group spill-over effects depending on their group outcomes across metropolitan areas and over time, and when they move across cities themselves.

Table 2 shows the definition of the variables in our earnings model. These variables are included in the specified categories of time-varying, time-invariant, exogenous, and endogenous. In our HT model specification and designation of endogenous and exogenous variables, we apply conventional knowledge based on the literature. While some judgement calls are needed in the designation of endogeneity, our selections are validated by statistical tests.

[Table 2 here]

Most importantly, the variable of interest – spatial network effect, based on country of origin – is identified as endogenous, due to potential location effects and location bias (Clark and Drinkwater 2000; Edin et al. 2003).

A second variable of interest, which the model controls for, is ethnic concentration (group geographic concentration based on country of origin) in each city. This variable has the conventional measure of the proportion of the population of a specific group to the total population size in the metropolitan area. This indicator varies by country of birth, metropolitan area, and year. We derived it from the census year previous to the wave of HILDA survey and we matched it with HILDA data.[8] Two positive features of this specification are that it is based on the entire population residing in each city and it provides a lagged measure of concentration and not the current measure, which reduces potential endogeneity.[9] This variable is also treated as endogenous due to immigrant location choice and unobservable factors correlated with this variable.

Third, due to potential unobserved factors (e.g., variation in ability) and correlation with the error term, human capital (skill level) and marriage are treated as endogenous, as they have been in previous economic analyses (e.g., Card 1999; García et al. 2008; Ruiz et al. 2010).

Furthermore, the model controls for endogenous migrants' location dynamics. We treat city dummies as endogenous due to potential unobserved characteristics of the city and earnings, such as a higher cost of housing or economic activity. In our panel data, we observe that a number of immigrants (about 5 percent of the sample) changed their city across the ten-year period, indicating an expected feedback effect of earnings on location choice. One of the advantages of the HT estimation is that we are able to use all of the exogenous variables in the model as instrumental variables to account for endogenous immigrants’ location choice.

Conventional human capital variables, such as years of experience (derived from: [age − age of completion of studies]), are included. The model also includes survey year fixed effects, and immigrant cohort arrival by decade, which corresponds to Australian immigration selection policy shifts. Auxiliary model specification tests validate the designation of these three group of variables as exogenous.

We examined a number of auxiliary models on our specifications and the choice of explanatory variables, and find that the results of the analysis are not sensitive to the variations in specification. For example, we estimated additional models with age and age-squared treated as exogenous, instead of years of experience (based on human capital theory), which we treat as potentially endogenous. We find that the coefficients for the network and ethnic concentration variables are not sensitive to this choice. We tested other variations of the model with the cohort (decade) of arrival considered as endogenous, but the results of interest were not sensitive to these variations.

We acknowledge that the individuals from the same country of origin may not necessarily know each other. But the individuals in the survey randomly represent others from the same country of origin. Other applications of the spatial methodology use a similar approach in establishing connections between individuals. Examples include Baltagi et al. (2017), who use rural origin to study rural migrants to large Chinese cities, and Lin et al. (2006), who use township and occupation to establish network effects in a study of national identity. In addition, Census data utilised for ethnic geographic concentration variables includes the entire population, and it provides an indication of the size and strength of group concentration in each metropolitan area.

VI Results

Results of both the conventional and extended HT models are provided in Table 3. The results in columns 1 and 3 are based on specifications of the conventional model and the results in columns 2 and 4 include the added spatial network weight matrix variable. These estimates have accounted for endogeneity of these two and other variables, as discussed earlier.

The models perform well in general and all human capital variables have the expected signs. We discuss the results based on the HT model first, and also report on comparative robustness checks based on OLS, FE, and RE estimations in Table A1 in the Appendix.

To statistically examine the validity of the HT estimation and the selection of the exogenous and endogenous variables for our analysis, we conducted the two conventional Hausman tests and the over-identification test[10]. The two-step Hausman tests (Baltagi et al. 2014; Breunig et al. 2013) examine whether or not the HT estimator is the preferred specification, rather than the fixed effects and random effect specifications. The first Hausman test distinguishes between the performances of the random effects model versus the fixed effects model. If the random effects model is rejected, then the second Hausman test is used. The second test compares the HT estimator to a fixed effects model, where the fixed effects model provides a benchmark for the HT estimator (e.g., Breunig et al. 2013). In the event that the second Hausman test cannot reject the null hypothesis that the two models are equivalent, then one can accept that the assumptions of the HT estimator are valid.

In our tests, the first Hausman test results reject the random effects model (p-value = 0.00001) and the second Hausman test cannot reject the null hypothesis that the fixed effects model and the HT estimator are identical (p-value = 0.9740). Therefore, the hypothesis cannot be rejected. Furthermore, from the over-identification test, the Sargan-Hansen statistic is 16.904 (p-value = 0.1108); therefore, the null hypothesis cannot be rejected, suggesting that the strong exogenous assumption of the HT estimators holds in our case. As a result, both tests strongly confirm the HT specification adopted for our analysis.

Based on our results (Table 3), immigrants benefit from spatial ethnic/cultural concentration (Tables 3 and A1). This result is consistent with the hypothesis that a greater concentration ratio provides greater markets and group-specific opportunities for the immigrant groups in their metropolitan area.

Notably, the results show a positive and significant network effect on immigrants' earnings, indicating that the quality of the resources of the group has an added and significant effect on immigrants' labour market performance. Based on our results in columns 3 and 4, we estimate a spatial spill-over effect of about 0.05, or about 5 percent for a 100 percent change in the network group's average economic resources. A comparison of columns 2 and 4 further indicates that when the network variable is excluded from the model, as in most earlier studies, the ethnic concentration variable combines both effects and it may be biased. In this case, as column 2 shows, the ethnic concentration variable is over estimated (a positive bias of about 11 percent in this case), compared to column 4.

[Table 3 here]

The comparative results based on pooled OLS (expected to be biased due to endogeneity), FE, RE, and IV estimations are presented in Table A1 (Appendix). All sets of results confirm positive independent effects from both the ethnic concentration and the network of economic resources variables, but larger impacts in the HT estimation results.

The other coefficients in the model are also compatible with theoretical expectations and the literature. The wage rate increases with work experience (in quadratic form) and education qualifications. In addition, immigrants from English-speaking countries have significantly higher hourly wages compared to immigrants from non-English-speaking countries. This effect, which is related to language fluency and its impact on earnings, is consistent with expectations and earlier findings (Chiswick and Miller 1999). It also confirms that immigrants from non-English-speaking countries have lower earnings while controlling for some observable and work-related human capital factors.

(i) Robustness Checks

Augmented HT model

As a part of our validity checks we examined the robustness of our results by applying an alternative specification. For that specification we added the spatially lagged exogenous variables (WX) on the right-hand side of the model for full interaction effects of the network variable with all other explanatory variables. This approach is consistent with Bramoulle et al.'s (2009) method to estimate the coefficient of social interaction term. The model is also in line with Cliff and Ord's (1981) extended spatial autoregressive (SAR) model. The model takes the form:

$$y_t = \rho W_t y_t + X_t\beta + \delta W_t X_t + Z\gamma + \varepsilon_t,\ t = 1,\ldots,T \qquad (4)$$

These results are provided in Table A2 (Appendix). The results confirm that our reduced-form model provides a consistent estimation of the network effect variable (Wy) coefficient across the Bramoulle et al. (2009) method and the Hausman and Taylor estimation methods. In the absence of omitted variable bias, the two methods are expected to provide similar results.

The results in columns 1 and 2 of Table A2 confirm that this is indeed the case for our results indicating that Models (2) and (3) reported in the previous section are correctly specified.

General Method of Moments (GMM) model

As an added part of our validity checks we examined the robustness of our results by applying an alternative estimation method based on GMM (Lee 2007; Baltagi et al. 2017). This approach adjusts for the endogeneity of the network variable, but not the other variables. As column 3 of Table A2 confirms, the results of interest on the network variable reported in Table 3 also correspond closely to this alternative estimation method.

Sample selection and attrition

As noted earlier in our discussion of data (Section III (i)), the HILDA survey has a remarkably high retention rate for the period of the analysis. In addition, as discussed earlier, we apply HILDA's longitudinal weights in all models. [11]

As a robustness check for selection into the sample, we also examined supplementary specifications to test the potential impact of selection on our results (Heckman 1979). We incorporated alternative instrument sets, including a set similar to Breunig et al. (2013).[12] The models performed well and passed the required tests. The results are consistent with the findings reported in the paper, notably for the network effect of interest. We find that the coefficient for the network economic variable (Wy) and ethnic concentration (EC) are both positive (0.048 and 0.042, respectively) and statistically significant, supporting our main results. The results are available in Table A3 in the Appendix.

The HT model adopted in this paper has the advantage of accounting for endogeneity of the main and other explanatory variables in the panel setting.

Including rural and small urban areas

Our analysis focuses on metropolitan areas. As a robustness check, we also estimated our model for the larger sample of immigrants that includes not only the metropolitan population, but also immigrants residing in small urban and rural areas. The HILDA data set provides this information for the population residing outside of the main metropolitan areas by state. The results are available in Table A4 in the Appendix. Our main reported coefficients for the network and ethnic concentration variables in metropolitan areas are larger than these auxiliary results based on the augmented sample including small towns and rural areas. For example, the coefficient for the network variable (Wy) in Table 3 (column 4) is 0.053, compared to 0.032 (Table A4, column 4). This result is consistent with the expectation that the network impact is greater in metropolitan areas where ethnic groups have greater concentrations and opportunities for using the economic resources of the network in the metropolitan settings. Our focus on the metropolitan population is in keeping with earlier studies. It also helps us isolate network and ethnic concentration effects of interest from potential larger urban area effects.

Alternative specification

In addition to alternative variable specifications (discussed in Section V (i)), we also examined models with other variations in the base model's variable specifications (similar to Breunig et al. 2013). We first estimated specifications without and then with the added network economic resource (Wy) and ethnic concentration (EC) variables. These models performed well. Again, the findings on the network and ethnic concentration effects were also consistent with the results in Table 3 (column 4). Notably, the coefficient for Wy is 0.052 (significant at at p value = 0.01), compared to the comparable coefficient of 0.053 in Table 3.

(ii). Results by Country-of-Origin Group and Skill Level

For a closer examination of network effects by country-of-origin groups, we estimated the model for the sample groups of the English-speaking countries (ESC) and non-English-speaking countries (NESC) and by skill level for high-skilled and less-skilled groups. Table 4 summarises the results. While both models performed well, the results show divergent results for NESC and ESC groups of immigrants and by skill level in terms of determining factors for immigrant earnings.

[Table 4 here]

Notably, we find that the network spill-over effect of immigrants' earnings is positive and significant for NESC immigrants (0.056 for the network economic variable Wy), compared with the same effect for ESC immigrants (0.042) that is statistically insignificant (columns 1 and 2 of Table 4). This result is consistent with the expectation that the strength and resources of immigrant geographic networks play a much greater role in the economic performance of immigrant minorities, in this case immigrants with a language that is different from the host country.

The impact of ethnic concentration (EC), based on ethnic group subsamples, is positive for both ESC and NESC groups, albeit weakly significant in the separate sub-samples (at p value = 0.10).

In addition, the results by skill level (columns 3 and 4 of Table 4) confirm a larger and significant positive impact of networks of resources for high-skilled workers (coefficient of 0.099 and highly significant). This finding is in line with the economic resources effect discussed above, as economic resources are empirically greater among high-skilled immigrants. [13] The impact of ethnic concentration (EC), based on skill-group subsamples, is positive for both groups, but again larger for high-skilled immigrants.

These results shed light on the economic significance of geographic ethnic concentration and networks of resources for NESC immigrants in overcoming some of the disadvantages these immigrants face in adapting to life in the host country. The positive and significant network spill-over effect for immigrants from NESC groups further indicate that greater concentration of immigrants would be most beneficial to the immigrant group when the ethnic networks of economic resources are richer and larger. Similarly, the positive coefficient of the network variable can explain lower earnings (a ghetto effect) when some groups' resources are significantly lower than other groups. The inclusion of the network variable provides a valid explanation for diverse results in the literature, where econometrically unobserved immigrant group resources are below or above average.

VII Conclusion

In this paper, we have augmented the conventional model of immigrant earnings and developed a new specification to examine the effect of ethnic-spatial networks of economic resources on immigrants' earnings. To the best of our knowledge, this is the first application of the spatial auto-regressive matrix approach of immigrant network of economic resources to the analysis of immigrant earnings in Australia.

We address the endogeneity of the ethnic-spatial network variable and other related covariates in the augmented immigrants' earnings model in the panel setting.

We find evidence of significant and positive co-dependence of results for immigrants. Notably, the network variable has a positive and significant spill-over effect on wage growth for immigrants from non-English-speaking backgrounds and high-skilled immigrants. The immigrant network of economic resources helps these groups of immigrants to achieve better economic performance than otherwise. At the same time, the model is consistent with explaining lower earnings growth over time when group economic resources are limited. These results are consistent with the hypotheses of network spill-over effects discussed in Section IV.

A policy implication of the results is that, for countries with skill-based immigration policies, ethnic geographic networks of economic resources and ethnic concentration can make positive economic contributions to the earnings of immigrants. The effect is especially prominent for NESC and high-skilled immigrants, highlighting a positive network spill-over effect for these groups.

Finally, we find that incorporating the group network of economic resources variable, and the co-dependence of economic outcomes for immigrant groups, provides additional estimation channels and useful insights in understanding immigrant earnings. Our results highlight that these effects can be particularly relevant for modelling and hypothesising earnings effects for the large group of immigrants with language origins that are different to the host country, as well as high-skilled immigrants in general.

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Appendix

Auxiliary Estimations

Table A1

Alternative Panel Data Estimation Methods (pooled OLS, FE, RE and HT results)
Dependent Variable: Log Hourly Wage (coefficients (standard errors))

	(1) Pooled OLS	(2) Random Effect	(3) Fixed Effect	(4) Hausman-Taylor IV
Network Effect (Weighted log Hourly Wage of spatial country-of-birth network (*Wy*)) $^{\phi}$	0.053*** (0.010)	0.054*** (0.013)	0.055** (0.024)	0.053** (0.022)
Ethnic Concentration$^{\phi}$	0.041*** (0.010)	0.016 (0.017)	0.144** (0.048)	0.132*** (0.039)
Other variables				
Experience	0.009 (0.010)	0.030*** (0.008)	0.040*** (0.012)	0.040*** (0.014)
Experience squared	–0.000 (0.000)	–0.000*** (0.000)	–0.001*** (0.000)	–0.001*** (0.000)
High skilled $^{\phi}$	0.237*** (0.022)	0.220*** (0.042)	0.279 (0.209)	0.368* (0.214)
Married $^{\phi}$	0.028 (0.021)	0.048 (0.042)		0.141 (0.204)
English-Speaking Country of Birth	0.593*** (0.120)	0.522*** (0.133)	0.495*** (0.148)	0.492*** (0.146)
Cohort 2001-2010	0.141** (0.048)	0.222** (0.097)		0.121 (0.138)
Cohort1991-2000	0.003 (0.037)	0.074 (0.083)		0.115 (0.103)
Cohort 1981-1990	0.054* (0.029)	0.042 (0.054)		0.098 (0.079)
Cohort 1971-1980	0.118*** (0.031)	0.138** (0.056)		0.210** (0.082)
Arrived before 1971		Reference Group		
City Fixed Effect $^{\phi}$	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2936	2936	2936	2936
sigma_u		0.360	0.561	0.922
sigma_e		0.290	0.302	0.301
rho		0.606	0.775	0.903

Wald chi2	534.4	18208.0

Notes:
Robust standard errors in brackets, where * p<0.10 ** p<0.05 *** p<0.01.
$^{\phi}$ Column (4) is the same as column 4, Table 3 ($^{\phi}$variables treated as endogenous in HT specification).
Sample: Full-time employed males, ages 25-64.
Source: HILDA-Release 10 (Wave 1-Wave 10).

Table A2

Alternative Specifications (Augmented HT and GMM Results
Dependent Variable: Log Hourly Wage (coefficients (standard errors))

	(1) Base HT Model Without WX	(2) Augmented HT Model With WX	(3) GMM Estimation
Network Effect (Weighted log Hourly Wage of spatial country-of-birth network (*Wy*)) $^{\phi}$	0.053**	0.050**	0.051**
	(0.022)	(0.020)	(0.023)
Ethnic Concentration $^{\phi}$	0.132***	0.103***	0.142***
	(0.039)	(0.035)	(0.010)
Other variables			
Experience	0.040****	0.041***	0.040***
	(0.014)	(0.012)	(0.005)
Experience squared	–0.001**	–0.001***	–0.001***
	(0.000)	(0.000)	(0.000)
High-Skilled $^{\phi}$	0.368*	0.369*	0.216***
	(0.214)	(0.208)	(0.020)
Married $^{\phi}$	0.141	0.043	0.025
	(0.204)	(0.054)	(0.018)
English-Speaking Country of Birth	0.492***	0.490***	0.583***
	(0.146)	(0.145)	(0.118)
Cohort 2001-2010	0.121	0.328*	0.114**
	(0.138)	(0.183)	(0.044)
Cohort1991-2000	0.115	0.173	0.014
	(0.103)	(0.123)	(0.030)
Cohort 1981-1990	0.098	0.105	0.024
	(0.079)	(0.095)	(0.022)
Cohort 1971-1980	0.210**	0.176*	0.099***
	(0.082)	(0.093)	(0.025)
Arrived before 1971		*Reference Group*	
City Fixed Effect $^{\phi}$	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*
Observations	2936	2936	2936
sigma_u	0.922	0.732	
sigma_e	0.301	0.300	
rho	0.903	0.856	
Wald chi2	18208.0	1.62e+06	2021.8

Notes:
The auxiliary model (2) is motivated by Bramoulle et al.'s (2009) approach. See Section VI (i) for further discussion (as in equation (4) in Section VI (i): $y_t = \rho W_t y_t + X_t\beta + \delta W_t X_t + Z\gamma + \varepsilon_t$, $t = 1,\dots,T$)
The base and augmented models include all of the explanatory variables as in Table 3.
Robust standard errors in brackets, where * p<0.10 ** p<0.05 *** p<0.01.
$^{\phi}$ Variables Network Effects, Ethnic concentration, Married, City fixed effects, and High-skilled are treated as endogenous in the HT setting as in Table 3.

The difference of coefficients obtained from (1) and (3) is about 0.002 which can be considered as statistically insignificant. The z-value of the difference (0.002) is about 0.069. The z-score is obtained by the method provided in this article: https://www.stata.com/statalist/archive/2012-08/msg00120.html

Sample: Full-time employed male immigrants ages 25-64.
Source: HILDA-Release 10 (Wave 1-Wave 10).

Table A3

Heckman Sample Selection Model

Ethnic Network Spill-overs and Immigrants' Earnings
Dependent Variable: Log Hourly Wage (coefficients (standard errors))

	Heckman Sample Selection Model
Network Effect (Weighted log Hourly Wage of spatial ethnic network (*Wy*))	0.048*** (0.005)
Ethnic Concentration	0.042*** (0.005)
Other variables	
Experience	0.012*** (0.003)
Experience squared	–0.000** (0.000)
High Skilled	0.246*** (0.013)
Married	–0.001 (0.014)
English-Speaking Country of Birth	0.602*** (0.014)
Cohort 2001-2010	–0.057* (0.031)
Cohort1991-2000	–0.007 (0.020)
Cohort 1981-1990	–0.003 (0.017)
Cohort 1971-1980	0.033* (0.019)
City Fixed Effect	*Yes*
Year Fixed Effect	*Yes*
Selection model	
Mortgage	0.232*** (0.029)
Presence of children of the age group of 0-4	0.108** (0.039)

Presence of children of the age group of 5-9	0.098**
	(0.039)
Presence of children of the age group of 10-14	0.011
	(0.037)
Presence of children of the age group of 15-24	–0.009
	(0.039)
Partners' Income	0.029**
	(0.011)
City Fixed Effect	*Yes*
Year Fixed Effect	*Yes*
athrho	0.828***
	(0.040)
lnsigma	–0.650***
	(0.013)
Observations	8555
sigma_u	
sigma_e	
rho	0.679
lambda	- 0.355
Wald chi2	2950.5

Notes:
Heckman Sample Selection model estimation.
Robust standard errors in brackets, where * p<0.10 ** p<0.05 *** p<0.01.

Cohort Effect base category is 'arrived prior to year 1971'.

The explanatory variables in the hourly earnings model are the same as in Table 3, column 4.

The explanatory variables in the Selection model (derived from HILDA) have the conventional specifications (e.g., Breunig et al. 2013), as follows: Partner's income; binary variables for whether the respondent had a mortgage; and 4 binary variables on the presence of children of the age groups of 0-4, 5-9, 10-14, and 15-14.

Sample: Full-time employed males, ages 25-64 (males, ages 25-64 in the Selection model).
Source: HILDA-Release 10 (Wave 1-Wave 10).

Table A4

Including Rural and Small Urban Areas

Ethnic Network Spill-overs and Immigrants' Earnings (with control for endogeneity)
Hausman–Taylor Panel Data Estimation

Dependent Variable: Log Hourly Wage (coefficients (standard errors))

	(1) Conventional Model	(2) Conventional Model	(3) Network Model	(4) Network Model
Network Effect (Weighted Hourly Wage of spatial ethnic network (*Wy*)) $^{\phi}$			0.031***	0.032***
			(0.008)	(0.008)
Ethnic Concentration $^{\phi}$		0.036**		0.039**
		(0.016)		(0.016)
Other variables				
Experience	0.021***	0.019***	0.021***	0.019***
	(0.007)	(0.007)	(0.007)	(0.007)
Experience squared	–0.000***	–0.000***	–0.000***	–0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
High Skilled $^{\phi}$	0.094	0.073	0.083	0.061
	(0.075)	(0.075)	(0.075)	(0.075)
Married $^{\phi}$	0.178	0.235	0.130	0.190
	(0.154)	(0.159)	(0.151)	(0.157)
English-Speaking Country of Birth	0.538***	0.534***	0.539***	0.534***
	(0.117)	(0.117)	(0.117)	(0.117)
Cohort Effects	*Yes*	*Yes*	*Yes*	*Yes*
City Fixed Effect $^{\phi}$	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6322	6322	6322	6322
sigma_u	0.577	0.594	0.560	0.578
sigma_e	0.318	0.318	0.318	0.318
rho	0.767	0.777	0.756	0.768
Wald chi2	1411.4	1403.8	1437.5	1429.9

Hausman–Taylor panel data estimation
Robust standard errors in brackets, where * p<0.10 ** p<0.05 *** p<0.01.
$^{\phi}$ Variables Network Effects, Ethnic concentration, Married, City fixed effects, and High-skilled are treated as endogenous.
Sample: Full-time employed males, ages 25-64, including individuals living in other small cities and rural areas in Australia.
Source: HILDA-Release 10 (Wave 1-Wave 10).

Supplementary APPENDIX (S1)

Technical Note

Specification and Identification of the Hausman-Taylor Model with a Spatial Lag Component

Consider first a model, which is essentially the same as that of Hausman and Taylor (1981):

$$y_{it} = x_{it}'\beta + z_i'\gamma + \varepsilon_{it}$$

where $i = 1,\ldots,N$ ("individuals") and $t = 1,\ldots,T$ ("time periods"), and x_{it}' and z_i' are $1 \times k$ and $1 \times g$ vectors of observations respectively on two sets of regressors, the first of which are time varying and the second are not, as indicated by the presence/absence of t subscripts; β and γ are the corresponding coefficient vectors. The disturbances ε_{it}, likewise consist of time varying and time invariant components:

$$\varepsilon_{it} = \alpha_i + \eta_{it}$$

where η_{it} are independent and identically distributed with $E[\eta_{it}] = 0$, $var[\eta_{it}] = \sigma_\eta^2$ and are jointly independent of all x_{js}, z_j and α_s for at all i, j, s, t. The time-invariant components α_i are, as in Hausman and Taylor (1981), independently distributed across individuals, with variance σ_α^2. This last assumption is important for the extension we consider below.

The regressors are partitioned as $x_{it}' = [x_{1it}' : x_{2it}']$, where the two sub-vectors of x_{it}' here are $k_1 \times 1$, $k_2 \times 1$, and $z_i' = [z_{1i}' : z_{2i}']$, with sub-vectors of order $g_1 \times 1$, $g_2 \times 1$ respectively. (β and γ are partitioned conformably as $\beta' = [\beta_1 : \beta_2']$, $\gamma' = [\gamma_1' : \gamma_2']$. The point of this partitioning is that x_{1jt}, and z_{1j} are assumed to be jointly independent of α_i, and so, in particular

$$E[\varepsilon_{it} \mid x_{1it}, z_{1i}] = E[\alpha_i \mid x_{it}, z_i] = 0,$$

which is important for the potential estimability of the entire coefficient vector $(\beta' : \gamma')$; but this conditional expectation property does not hold for x_{2it} and z_{2i}, and

$$E[\varepsilon_{it} \mid x_{2it}, z_{2i}] = E[\alpha_i \mid x_{2it}, z_{2i}] \neq 0.$$

It is convenient in the present case to stack the model by collecting observations on individuals for each time period (rather than over time by individuals as Hausman and Taylor do) and write

$$y_t = X_t\beta + Z\gamma + \varepsilon_t$$

where y_t, ε_t are $N \times 1$ vectors, and X_t, and Z are $N \times k$ and $N \times g$ respectively,

$\varepsilon_t = \alpha + \eta_t$

here α is the $N \times 1$ vector of time-invariant disturbances (unobserved individual specific effects) and $X_t = [X_{1t} : X_{2t}]$, $Z = [Z_1 : Z_2]$, with β and γ partitioned as above. Note for each t, the elements of ε are mutually uncorrelated and have the same variance, since the elements of both α and η_t have this structure; although α is replicated over time periods.

In the standard HT set up the time-invariant property of α provides instruments which are sufficient for estimation of β, but the time invariant property of Z means that γ is not estimable on the basis of these alone. If other instruments are available – in the form of X_{1t} – these, combined with the time invariance of α, can be sufficient for IV estimation of β and γ.

To see this stacked again across time periods to get

$y = X\beta + (\iota_N \otimes Z)\gamma + \varepsilon$

Here, $\varepsilon = (\iota_N \otimes \alpha) + \eta$ and $\otimes$ denotes Kronecker product. So $\iota_N \otimes \alpha$ is N replicates of α, one on top of another and η is the $NT \times 1$ vector consisting of the T $N \times 1$ vectors η_t one on top of another. Similarly, X is the X_t's stacked one on top of another: $X' = [X_1' \ldots X_T']$ and $X = [X_1 : X_2]$, while $\iota \otimes Z$ is N replicates of Z stacked one on top of another, and $\iota_N \otimes Z = \iota_N \otimes [Z_1 : Z_2]$.

Next, let Q be the $NT \times NT$ matrix defined by

$Q = I_{NT} - \iota_N\iota_N' \otimes I_T/N$

so that for the stacked model Q annihilates Z in the sense that $QZ = 0$ and also annihilates the time invariant component, $\iota \otimes \alpha$ of ε, i.e, $Q(\iota_N \otimes \alpha) = 0$.

The matrix of observations on the set of potential instrumental variables is $[Q: X_1: Z_1]$, and the necessary order condition obtained by Hausman and Taylor (1981, Proposition 3.2, p. 1385) for the identification of both β and γ is

$k_1 \geq g_2$ (see Table 2)

Now consider an extension of this model to accommodate “spatial lags” in the dependent variable (but without spatial autocorrelation in the disturbances as considered in, for example, Baltagi (2013, p. 325) and Baltagi and Liu (2011).

The model for each t is now

$$y_t = \rho\, W_t y_t + X_t\beta + Z\gamma + \varepsilon_t, \quad t = 1,\ldots,T$$

where X_t, Z, and $\varepsilon_t = \alpha + \eta_t$ as before, and where W_t are T known $N \times N$ matrices of weights (each with zeros on the main diagonal); these may or may not be the same for all t; ρ is an unknown coefficient, to be estimated alongside β and γ.

Next, note that on the right-hand side of the model

$$W_t y_t = \rho\, W_t[X_t\beta + Z\gamma] + W_t\varepsilon_t$$

and observe that any given element of $W_t\varepsilon_t$ is independent of the corresponding element of ε_t, because of the zero diagonal elements of W_t and the mutual independence, for each t, of the N elements of the vector ε_t.

It remains to deal with potential correlation between corresponding elements of W_tX_t and ε_t and also between corresponding elements of W_tZ and ε_t. Because each diagonal element of W_t is zero, such correlations would have to take the form of dependencies across individuals, and assuming this away may be reasonable; and if so, then W_ty_t can be absorbed into X_{1t} (or conceivably into Z_1 under sufficient time invariance); and if not, then into X_{2t} (or conceivably into Z_2).

The implication of this is that the Hausman-Taylor order condition for the identification/estimability of ρ, β, γ in the most pessimistic case is strengthened to

$$k_1 \geq g_2 + 1$$

(where k_1 is the number of time-varying exogenous variables, and g_2 is the number of the time-invariant endogenous variables) since the presence of W_ty_t effectively increases g_2 by one, and for the most optimistic case the condition is weakened to

$$k_1 + 1 \geq g_2$$

since the presence of W_ty_t effectively increases k_1 by one. Conceivably the condition undergoes no change: this is so when it has the effect of increasing k_2, arguably the most likely scenario, or g_1.

It is possible therefore to proceed simply by incorporating Wy_t into X_{1t}, X_{2t} or conceivably Z_1, Z_2. Note that time invariance of W_t is not crucial, because W_ty_t will almost certainly be time varying, and so is likely to be allocated to either X_{1t} or into X_{2t}, rather than to Z_1 or Z_2. Once this decision has been made, estimation of ρ, β, γ can proceed exactly as in Hausman-Taylor (1981). For the model we estimate (see

Table 2 and the corresponding discussion in Section 5), we have $k = 19$, $k_1 = 11$, $g = 6$, $g_2 = 1$, so the condition is satisfied, even in the most pessimistic case. The classification of each of the variables we use appears in parentheses in Table 2, after the variable descriptions.

The stacked form of the model takes the form

$$y = \rho\, \mathrm{diag}[W_t]y + X\beta + (\iota_N \otimes Z)\gamma + \varepsilon$$

where, $\mathrm{diag}[W_t]$ is a $NT \times NT$ block diagonal matrix with T diagonal blocks, the t^{th} being W_t; the other terms are as before. Note that the reduced form of the full model is

$$y = [I - \rho\, \mathrm{diag}[W_t]]^{-1}X\beta + [I - \rho\, \mathrm{diag}[W_t]]^{-1}(\iota_N \otimes Z)\gamma + [I - \rho\, \mathrm{diag}[W_t]]^{-1}\varepsilon$$

assuming that $[I - \rho\, \mathrm{diag}[W_t]]$ is invertible. The question of the identification of ρ, β, γ within this reduced form can then be approached along the lines of Bramouille et al. (2009). Identification fails if $(\rho^o, \beta^o, \gamma^o)$ and $(\rho^*, \beta^*, \gamma^*)$ are observationally equivalent, and this is easily seen to happen if and only if

$$[I - \rho^o\, \mathrm{diag}[W_t]](X\beta^* + (\iota_N \otimes Z)\gamma^*) = [I - \rho^* \mathrm{diag}[W_t]]](X\beta^o + (\iota_N \otimes Z)\gamma^o)$$

which implies that the columns of $[I - \lambda\, \mathrm{diag}[W_t]](X : (\iota_N \otimes Z))$ and $\mathrm{diag}[W_t](X : (\iota_N \otimes Z))$ are linearly dependent, where λ is a scalar (which here is equal to $\rho^* - \rho^o$). Given that $(X : (\iota_N \otimes Z))$ has full column rank – a minimal identifiability requirement even in the absence of the spatial autocorrelation feature – this implies (but is not implied by) singularity of $[I – (\lambda + 1)\mathrm{diag}[W_t]]$, which is evidently problematical given the assumed invertibility of $[I - \rho\, \mathrm{diag}[W_t]]$. Therefore, lack of identification in this setting is not a cause for concern.

Table 1
Descriptive Statistics

	Pooled	By Language		By Skill Level	
		ESC*	NESC*	High Skilled**	Less Skilled**
High Skilled (%)	42.8	37. 1	48.7	/	/
Married (%)	73.2	70.8	75.7	75.0	70.3
Experience (years, mean)	30.5	31.3	29.6	26.9	33.1
Log of Real Hourly Wage in Main Job	3.1	3.2	3.1	3.3	3.0
Ethnic concentration (Log of country-of-birth group concentration)	–4.0	–3.5	–5.0	–4.5	–3.9
Born in Main English-Speaking Countries (ESC) (%)	50.6	/	/	43.8	55.8
Born in the UK and Ireland (%)	33.8	66.8	/	26.8	39.1
Born in New Zealand (%)	10.6	20.9	/	7.08	13.2
Born in Other ESC Countries (%)	6.2	12.3	/	10.0	3.4
Born in Non-English-Speaking Countries (NESC) (%)	49.4	/	/	56.2	44.3
Born in Asia (%)	25.5	/	51.6	31.3	21.1
Born in Other NESC Countries (%)	23.9	/	48.5	24.9	23.1
Arrived between 2001 and 2010 (%)	2.7	2.5	3.0	4.2	1.6
Arrived between 1991 and 2000 (%)	24.0	16.8	31.3	32.8	17.4
Arrived between 1981 and 1990 (%)	31.4	30.1	32.8	34.4	29.2
Arrived between 1971 and 1980 (%)	19.5	19.9	19.2	15.1	22.8
Arrived before 1971 (%)	22.4	30.8	13.8	13.5	29.0
Number of observations	2936	1486	1450	1256	1680

Notes:

The definition of all variables is available in Table 2.

* ESC and NESC respectively refer to English-speaking and non-English-speaking country of birth.

**High-Skilled refers to a Bachelor’s or a higher degree, and Less-Skilled refers to below that level of education.

Real hourly wage (base year 2009).

Sample: Full-time employed male immigrants, ages 25-64.

Source: HILDA-Release 10 (Wave 1-Wave 10).

Table 2

Variable List and Definitions

Dependent Variable: Log Hourly Wage

Time-varying exogenous (X_1)	***The number of time-varying exogenous variables k_1=11***
Experience	In years (potential experience (age- age at completion of studies)).
Experience – squared	
Year (survey wave) fixed effects: Waves 2-10	Nine Binary Variables=1 if the observation comes from survey years 2, 3, 4, .. 10. (Wave 1 is the base group).
Time-varying endogenous (X_2)	***The number of time-varying endogenous variables k_2=8***
Network Effect (*Wy*)	The weighted (average) logarithm of hourly wage of an individual's country-of-birth spatial network (excludes the respondent's wage), by city, country of birth, and year t. This variable is derived from HILDA data.
Ethnic Concentration	The proportion of the population of a specific country-of-birth group to the total population size in the metropolitan area at time t-k, derived from the Population Census (1996, 2001, 2006) and matched with the panel data with a lag by city/ for each country of birth/year.
High-Skilled	Binary variable, equal to one if the individual had completed at least a Bachelor degree, Advanced Certificate, or Post-graduate degree.
City fixed effects:	Five Binary Variables= 1 if lives in the city at time t (Sydney; Melbourne; Brisbane; Perth; Adelaide; base group is ACT (Canberra)).
Time-invariant exogenous (Z_1)	***The number of time-invariant exogenous variables g_1=5***
English-Speaking Country of Birth (ESC)	Binary Variable, equal to one if the individual was born in one of the English-Speaking Countries (United Kingdom, New Zealand, Canada, USA, Ireland and South Africa).
Arrived 2001-2010	Four Binary Variables =1 if arrived between ((2001 – 2010); (1991-2000); (1981-1990); (1971-1980); base group arrived before 1971).
Time-invariant endogenous (Z_2)	***The number of time-invariant endogenous variables g_2=1***
Married	Binary Variable, equal to one if the individual is married prior to first being included in the survey.

Notes:

1. We use Xs and Zs to label the four categories of variables in the Hausman and Taylor model, and in the discussion on specification and identification of the HT model with a spatial lag component (*Technical Note*, Supplementary Appendix).
2. The above X and Z and endogeneity designations are statistically supported at highly significant levels (Two-step Hausman and over-identification tests, as discussed in Section VI.

Table 3

Ethnic Network Spill-overs and Immigrants' Earnings (with control for endogeneity)
Hausman–Taylor Panel Data Estimation

Dependent Variable: Log Hourly Wage

	(1) Conventional Model	(2) Conventional Model	(3) Network Model	(4) Network Model
Network Effect (Weighted log Hourly Wage of spatial ethnic network (*Wy*)) $^{\phi}$			0.057**	0.053**
			(0.022)	(0.022)
Ethnic Concentration $^{\phi}$		0.146***		0.132***
		(0.042)		(0.039)
Other variables				
Experience	0.042**	0.039**	0.043**	0.040**
	(0.015)	(0.014)	(0.015)	(0.014)
Experience squared	–0.001**	–0.001**	–0.001**	–0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
High- Skilled $^{\phi}$	0.384*	0.362*	0.386*	0.368*
	(0.201)	(0.205)	(0.210)	(0.214)
Married $^{\phi}$	0.223	0.234	0.124	0.141
	(0.182)	(0.203)	(0.187)	(0.204)
English-Speaking Country of Birth (ESC)	0.496***	0.490***	0.498***	0.492***
	(0.146)	(0.146)	(0.145)	(0.146)
Cohort 2001-2010	0.185	0.171	0.130	0.121
	(0.130)	(0.144)	(0.126)	(0.138)
Cohort1991-2000	0.048	0.161	0.009	0.115
	(0.091)	(0.106)	(0.092)	(0.103)
Cohort 1981-1990	0.031	0.116	0.021	0.098
	(0.069)	(0.083)	(0.066)	(0.079)
Cohort 1971-1980	0.162**	0.243***	0.134*	0.210**
	(0.069)	(0.082)	(0.070)	(0.082)
Arrived before 1971	*Reference group*			
City Fixed Effect $^{\phi}$	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2936	2936	2936	2936
sigma_u	0.795	0.947	0.780	0.922
sigma_e	0.303	0.302	0.302	0.301
rho	0.873	0.908	0.870	0.903
Wald chi2	21656.9	16901.6	23919.6	18208.0

Notes:
Hausman–Taylor panel data estimation
Robust standard errors in brackets, where * p<0.10 ** p<0.05 *** p<0.01.

$^{\phi}$ Variables Network Effects, Ethnic concentration, Married, City fixed effects, and High-skilled are treated as endogenous.
Sample: Full-time employed males, ages 25-64.
Source: HILDA-Release 10 (Wave 1-Wave 10).

Table 4

Ethnic Network Spill-overs and Immigrants' Earnings by Language and Skill Groups (with control for endogeneity) Hausman–Taylor Panel Data Estimation

Dependent Variable: Log Hourly Wage

	By Language Group		By Skill Level	
	ESC	NESC	High Skilled	Low Skilled
Network Effect (Weighted log Hourly Wage of spatial ethnic network (*Wy*)) $^{\phi}$	0.042 (0.050)	0.056** (0.026)	0.099*** (0.035)	0.038 (0.027)
Ethnic Concentration $^{\phi}$	0.38* (0.212)	0.096* (0.049)	0.170** (0.084)	0.121*** (0.045)
Other variables				
Experience	0.091*** (0.028)	0.040* (0.022)	0.079*** (0.027)	0.012 (0.016)
Experience squared	–0.001*** (0.0003)	–0.001*** (0.0003)	–0.001** (0.000)	–0.000 (0.000)
High Skilled $^{\phi}$	0.326** (0.130)	0.609* (0.338)		
Married $^{\phi}$	–0.466 (0.477)	0.227 (0.342)	–0.940** (0.424)	–0.067 (0.273)
English-Speaking Country of Birth (ESC)			0.514*** (0.199)	0.472*** (0.137)
Cohort 2001-2010	0.721** (0.321)	0.250 (0.213)	0.279 (0.400)	–0.072 (0.487)
Cohort1991-2000	0.836*** (0.287)	0.245* (0.131)	0.190 (0.223)	0.175 (0.122)
Cohort 1981-1990	0.364*** (0.131)	0.206 (0.135)	0.496** (0.199)	–0.008 (0.114)
Cohort 1971-1980	0.581*** (0.160)	0.096 (0.113)	0.339 (0.211)	0.136 (0.157)
Arrived before 1971		*Reference group*		
City Fixed Effect $^{\phi}$	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1486	1450	1256	1680
sigma_u	1.727	0.545	0.713	0.527
sigma_e	0.299	0.311	0.340	0.263
rho	0.971	0.730	0.815	0.801
Wald chi2	2612.9	10249.0	5052.3	7447.0

Notes:

Robust standard errors in brackets, where * p<0.10 ** p<0.05 *** p<0.01.

$^{\phi}$ Variables Network Effects, Ethnic concentration, Married, City fixed effects, and High-skilled are treated as endogenous.

Sample: Full-time employed males, ages 25-64.

Source: HILDA-Release 10 (Wave 1-Wave 10).

Notes

1. The dynamic spatial lag of order-one is applied in this study for socio-economic spill-over effects of immigrants from the same country of birth who reside in the same metropolitan area.

2. Selection of the age group as older than 24 years of age is useful in considering the group beyond university studies.

3. According to the definition adopted by the HILDA survey, the "Main English Speaking Countries" are United Kingdom, New Zealand, Canada, USA, Ireland, and South Africa.

4. For interested readers, the *Supporting Information* file for this paper provides further details on the model's formulation and identification strategy.

5. The Moran I's test confirms spatial auto-correlation in our case.

6. In a separate literature on the impact of social interactions on peer effects, the issue of interest incorporates separating the impact of the network per se (correlated and peer endogenous effects) from exogenous (or contextual) effects (e.g., Manski 1993). However, a number of spatial analyses in other contexts are interested in the correlation of outcomes, and they incorporate the simultaneous generation of outcomes, and are less concerned with separating these components (Goetzke 2008; LeSage and Pace 2009; Baltagi 2013; Baltagi et al. 2017). Our analysis in this paper has features of the second group of studies to incorporate simultaneous data generation and group interaction of outcomes.

7. Baltagi et al. (2014) apply the spatial Hausman-Taylor model, positioning the spatial lag as a component of the error structure. Then Baltagi et al. (2017) positioned it as a stand-alone variable. In our model, we incorporate the network variable (spatial lag component) in the model (as in equations (1) and (2) above) as in Goetzke (2008), LeSage and Pace (2009), Baltagi and Liu (2011), and Baltagi et al. (2017).

8. Australian Population Census years of 1996, 2001, and 2006 were used. The 1996 Census is used in the construction of the lagged EC variable for the 2001 to 2002 years; the 2001 Census for years 2003 to 2006; and the 2006 Census for years 2007 to 2010.

9. We also examined using an alternative measure of geographic ethnic concentration per year based on HILDA data. The results are generally compatible, but the measure we employ based on the Census data has clear advantages by representing the entire population of immigrants and native-born in each of the major cities, and could be incorporated in lagged form.

10. The Stata command "hausman" is used for the Hausman test and "xtoverid" is used for the over-identification test.

11. We have assessed results with and without HILDA's recommended longitudinal weights applied. When weights are applied (in the reported results), standard errors of coefficients become relatively larger. Hence, our conclusions from results applying the recommended weights are based on a more representative set of results.

12. These instruments (as in Breunig et al. 2013) are (whether or not the respondent had a mortgage; partner's income; and 4 binary variables on the presence of children of the age group of 0-4, 5-9, 10-14, 15-14). The results are available in Table A3 in the Appendix.

13. An alternative selection of sub-samples based on white-collar and blue-collar occupations confirms this positive result for high-skilled workers. For white-collar occupations, the network variable (W_y) and ethnic concentration (EC) coefficients are positive and

significant (respectively at 0.073 (p value=0.05) and 0.159 (p value= 0.01). The effects for blue-collar immigrants are insignificant, similar to those for the less-skilled sub-sample.