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Abstract

The aim of this paper is to empirically test the impact of social contacts on the individual unemployment risk and the probability of persisting unemployed over time controlling for the local context where the individual lives and creates friendships. We present evidence for a highly significant impact of social contacts on individual unemployment risk: social contacts reduce both the unemployment risk and the state dependence in unemployment. The disadvantage from having been unemployed in the previous period is smaller for individual with many social contacts and larger for individuals with limited social contacts. We assume that social interactions happen mainly locally in the neighborhood. We present evidence that neighborhood deprivation increases the individual unemployment risk, while neighborhood cohesion reduces the probability of unemployment in deprived neighborhood. These findings are consistent with the idea that individuals obtain information about job opportunities through a network of social contacts and unemployment may lead to a decay of social capital, making it more difficult to find employment in future periods.

JEL Codes: J64, C23, A14

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1. Introduction

The aim of this paper is to empirically test the impact of social contacts on the individual's probability of being jobless and the probability of persisting unemployed over time controlling for the local context where the individual lives and creates friendships.

It is a well-established finding that Individuals who are unemployed in one period are more likely to be unemployed in future periods. Such a relationship may be due to two fundamentally different mechanisms (Heckman, 1981). First, individuals who are unemployed in one period could have observed or unobserved characteristics that make them particularly vulnerable to unemployment. If some of these characteristics are persistent over time, they will also increase the unemployment risk of future periods, creating a spurious relationship between current and future unemployment. Second, the unemployment experience of one period could have a genuine causal effect on the unemployment risk of future periods in the sense that past unemployment causally increases the unemployment risk of future periods: this is usually called true state dependence.

Previous literature point out different mechanisms that may give rise to true state dependence: disincentive effects of unemployment insurance may lead the unemployed to postpone accepting job offers (see e.g. Mortensen (1977) and Burdett (1979)); unemployment experiences may be associated with processes of discouragement reducing search efforts and therefore increasing the risk of remaining unemployed (Clark et al. (2001)); unemployment may lead to a decay of human capital, making it more difficult to find employment in future periods (Mincer and Polachek (1974), Pissarides (1992)); individuals who are unemployed face systematically lower chances of being hired because employers interpret their unemployment as a negative signal (Biewen and Steffes, 2010).

The purpose of this paper is to contribute to this literature empirically testing another possible factor contributing to the persistence in unemployment dynamics: social contacts. It is well documented that people strongly rely on networks to find a job and that personal contacts and acquaintances play an important role in individual's job search and obtaining information about job opportunities (Montgomery, 1991; Granovetter, 1995; Ioannides and Loury, 2004; Calvo-Armengol and Jackson 2004 and 2007; Cingano and Rosolia, 2012; Zenou, 2015; Jackson et al. 2016 and 2017). Persistence in network's characteristics can impact on the unemployment risk and creates a spurious relationship between current and future unemployment. True state dependence can emerge when unemployment may lead to a decay of social capital, making it more difficult to find employment in future periods.

Calvo-Armengol and Jackson (2004) develop a model where individuals obtain information about job opportunities through an explicitly modeled network of social contacts. In the model, any individual hears about a job opening with a certain probability. If the individual is unemployed, she/he will take the job. If the individual is employed, she/he will pass the information along to a friend, relative, or acquaintance who is unemployed. Information flows only between individuals who known each other. In this model, the probability of obtaining a job decreases in the length of time that an agent has been unemployed: unemployment exhibits duration dependence and persistence. A longer history of unemployment is more likely to come when the direct and indirect connections of an individual are unemployed. Thus, seeing a long spell of unemployment for some individual leads to a high conditional expectation that the individual's contacts are unemployed. This in turn leads to a lower probability of obtaining information about jobs through the social contacts. Thus, controlling for the state of the network should help explain persistence in unemployment. We test this empirically in our paper.

But what does "controlling for the state of the network" mean? According Calvo-Armengol and Jackson, persistence in unemployment depends on network size and status of other individuals in the network. Given the size of the network, the probability that information ends up in individual's hands is low if the percentage of unemployed connections in the network is high (individuals face relatively more competition for information). In other word, if friends of individual's friends are employed rather unemployed, then the individual has a higher chance of being the one that friends will pass information to. Increasing the size of the networks increases the probability of receiving information only if new employed connections are added. In our paper, we control for "*social contacts*" a variable that gives information on the network size and the intensity of the interactions in the network (e.g. more interactions imply faster spread of the information in the network). We will also control for the status of the other individuals in the network observing that networks correlate with location and, therefore, location characteristics gives information on the status of the members of the network. In particular, we observe that social interactions happen often locally in the neighborhood where individuals live. Community participation generates social contacts and creates friendships. Thus, individuals rely on neighbors to obtain information about jobs (Bayer, Ross, and Topa 2008) and a longer history of unemployment is more likely to come when connections of an individual are mainly local in neighborhoods with high unemployment rates.[2] More in general, social contacts in deprived neighborhoods could be less effective for employment chances than the more bridging contacts (Putnam, 2000) in not-deprived neighborhoods because deprived neighborhood's lack the necessary job-related resources. Thus, residents of disadvantaged neighborhoods may be more likely to be unemployed and persist longer in unemployment due to lack of access to resourceful networks that hold information about job opportunities or neighborhood peer influences that undermine an effective job search. [3] Therefore, we control for "*neighborhood deprivation*". However, we also consider that social cohesion in the neighborhood (e.g., in terms of trust and willingness to help) can affect the spread of information in the neighborhood. Thus, we control for "*neighborhood cohesion*". We are especially interested in testing whether social cohesion in deprived neighborhoods can mediate the impact of the neighborhood's lack of job-related resources (Custers, 2019; Basher and Bramley, 2019; Pinkster, 2014; Tersteeg et al., 2015).

In our paper, we use 2006-2017 data from the Household Income and Labour Dynamics in Australia (HILDA) survey and we focus on young people aged [15,24] since the Australia's youth unemployment sat more than double the overall unemployment rate (ranging from 8.8% in 2008 to 13.3% in 2014)[4]. Our findings indicates that social contacts reduce both the probability of experiencing unemployment and the impact of past unemployment on the unemployment risk of future periods. However, social contacts seem be less effective in reducing unemployment persistence in deprived neighborhoods. Our results also show that neighborhood deprivation increases the probability of experiencing unemployment, while neighborhood cohesion reduces the probability of jobless in deprived neighborhood. In particular, the positive impact of neighborhood cohesion totally overcome the negative impact of neighborhood deprivation outside the major cities.

The rest of the paper is structured as follows. In section 2 we give details on our econometric setup. Section 3 describes our data, while section 4 discusses our empirical results. Section 5 concludes.

1. Econometric model

We use a dynamic binary choice model to model the evolution of individual unemployment status over time. Our main model is a dynamic, correlated random-effects probit model in the form popularized by Wooldridge (2005).

For individual *i* observed from time *t* = 1 to (as in our case) t = 3, the conditional probability that an event (unemployment) occurs is

$$(1) \qquad P(y_{it} = 1 \,|y_{it-1},\ldots,y_{io},z_i,c_i) = \emptyset(z_{it}\gamma + \rho y_{it-} + c_i)$$

[2] Not just residing in a disadvantaged neighborhood, but living there with all one's friends, prevents individuals from re-entering employment (Vandecasteele and Fasang, 2021).

[3] Residents of disadvantaged neighborhoods may be more likely to be unemployed also for the following reasons (Vandecasteele and Fasang, 2021): employer discrimination based on neighborhood; a spatial mismatch resulting from a lack of local jobs coupled with poor transportation connections; and, a lack of local institutional and social services that may help in the job search.

[4] OECD data

where Ø is the probit distribution, the dependent variable y_{it} is the unemployment status of individual *i* at time *t*, γ and ρ are the parameters to be estimated, z_i and z_{it} are, respectively, vectors of time-constant and time-varying explanatory variables, and c_i is the individual specific effect (modeled as random effects).
Quoting Woolddridge (2005, 41) himself, the assumptions implied by this equation are the following: "First, the dynamics are first order, once z_{it} and c_i are also conditioned on; second, the unobserved effect is additive inside the distribution function, Ø; third, z_{it} satisfies a strict exogeneity assumption.".
As suggested by Wooldridge (2005), the parameters in equation (1) can be consistently estimated by assuming a density for the individual specific effect given the unemployment initial condition, y_{i0}, and the time-constant explanatory variables, z_i. Thus, Wooldridge offers a solution to the initial condition problem. The latter may arise when the start of the observation period does not coincide with the start of the stochastic process generating individual jobless experiences (i.e. Arulampalam et al, 2000; Heckman, 1981). In other words, individuals could experience unemployment before the period under study and, therefore, individuals excluded at the start of the observation period may be there because of an earlier history of unemployment or because of some characteristics affecting their unemployment propensity. But, "finding the individual specific effect distribution conditional on the initial value (and the observed history of strictly exogenous explanatory variables)" permits to account for the correlation between the individual specific effects (that are all unobserved individual determinants of unemployment and are time-invariant) and the levels of unemployment experienced by the individuals in the initial period (Wooldridge, 2005). Moreover, it is also possible to allow for the correlation between unobserved and observed individual characteristics. For example, if ability is an unobserved factor, lack of ability may be the cause of the current unemployment, but it may also be correlated with jobless experienced by the individual at the initial period and the level of education achieved by the same individual. Therefore, we assume that

(2) $$c_i | y_{i0}, z_i \sim Normal(\alpha_0 + \alpha_1 y_{i0} + z_i \alpha_2, \sigma_\alpha^2)$$

where α_0, α_1 and α_2 are parameters to be estimated and σ_a^2 is the conditional standard deviation of the individual specific effect, c_i. Note that the vector z_i appears in (2), and not on the right hand side of (1), because otherwise we could not identify the coefficients for the time constant covariates. Among the time constant variables, we include the network state observed at t=0 (in terms of network size and status of other individuals in the network) as well as neighborhood cohesion. Given (1) and (2), we can write the conditional density for the conditional distribution and maximize the density obtained integrating the above equation with respect to the normal distribution in equation (2) in order to estimate the parameters γ, ρ, α_0, α_1, α_2, σ_a^2**.** The estimation is consistent only under the hypothesis that the model is correctly specified.
The latent variable version of the model described in (1) and (2) is the following

(3) $$y_{it}^* = z_{it}\gamma + \rho y_{it-} + \alpha_0 + \alpha_1 y_{i0} + z_i \alpha_2 + a_i + u_{it}$$

where u_{it} is a zero mean and constant variance error term. Information about the direction of the relationship between unobserved individual characteristics and unemployment at the initial period is given by the estimate of α_1. The estimate of σ_a^2 indicates the size of the dispersion that is attributable to the unobserved heterogeneity.
In the model, the value of ρ determines whether the unemployment sequence $\{y_{it}\}$ features true state dependence. In other words, it determines whether experiencing unemployment in a specific year, in itself, increases the risk of unemployment in subsequent years. In particular, if $\rho > 0$, then experiencing unemployment at time $t-1$, $y_{it-1} = 1$, increases the chance to experience unemployment at time *t* ($y_{it} = 1$). As discussed above, this may be due to different mechanisms such as disincentives of unemployment insurance, loss of skills and motivation, stigmatization and loss of social capital.

However, if the disadvantage from having been unemployed in the previous period is larger for individuals with limited social contacts and smaller for individuals many social contacts, this points to a role for the social capital in determining true state dependence, as disincentives of unemployment insurance, loss of skills and motivation should be independent of the network state. Stigmatization effect could be related to the network state but with the relation showing a opposite sign. In order to test this hypothesis, we also estimate

$$y_{it}^* = z_{it}\gamma + \rho_1 y_{it-1} + \rho_2 y_{it-1} network\_state_0 + \alpha_0 + \alpha_1 y_{i0} + z_i\alpha_2 + a_i + u_{it} \tag{4}$$

where past unemployment status is interacted with the network state (in terms of social contacts and social contacts in deprived neighborhoods).[5]

Finally, note that Wooldridge's method has some advantages in facing selection and attrition problems (e.g. problems that may arise using balanced data). In particular, as explained in Wooldridge (2005; pp. 44), it allows the selection and attrition to depend on the initial conditions and, therefore, it allows attrition to differ across initial unemployment. In particular, individuals with different initial statuses are allowed to have different missing data probabilities. Thus, we consider selection and attrition without explicitly modelling them as a function of the initial conditions. As a result, the analysis is less complicated and it compensates for the potential loss of information from using a balanced panel. Moreover, in the conditional MLE we can ignore any stratification that is a function of the initial unemployment and of the time-invariant explanatory variable: In fact, using sampling weights leads to a loss of efficiency.

2. Data and main variables

For our analysis we use the 2006-2017 Household, Income and Labour Dynamics in Australia (HILDA) data. The HILDA survey has been conducted annually since 2001 and is a household-based panel study that collects information about economic and personal wellbeing, labor market dynamics and family life. It aims to tell the stories of a representative group of Australians over the course of their lives. All household members aged 15 or over are invited for participation in the survey. The same households are re-interviewed every year, with new household members (over 15 years of age) and children turning 15 included in these interviews, and original household members who leave the household in a subsequent year are followed and re-interviewed as well, including any children who leave the parental home. In 2011 a top-up sample was added to the main sample of 2001. A detailed description of the HILDA survey and data is available in Summerfield et al. (2020).

Our sample of analysis includes all individuals who are aged [15,24] at the beginning of the period of analysis (t=0) and participate in the labor market during the following three years (t=1, 2 and 3). Three samples are considered defining as initial period (t=0) the following waves: 2006, 2010 and 2014. These are the only waves that collects detailed information on social contacts and neighborhood characteristics.[6] Our final (balanced) sample consists of 3043 individuals.

The dependent variable of our analysis is individual unemployment defined using information on the current labor force status (employed, unemployed and not in the labor force). As explanatory variables of unemployment risk in a given period we consider gender, age in years, marital status (or having a de facto partner), children in the household, educational level (a dummy "high education" equal to one if the education level is Technical and Further Education, Bachelors or Postgraduate), immigration status (at least one parent is not Australian born), Aboriginal or Torres Strait Islander origin, social contacts,

[5] Since this variable is time variant, it appears on the right hand side of (1)

[6] Details information on social contacts and neighborhood characteristics are also collected in 2018, but data on the following three years are not yet available

neighborhood deprivation and neighborhood cohesion. We also include a full set of region dummies[7] as well as dummies indicating the period and the sample.[8] We also use the Australian standard geographical classification system to include area dummies indicating major cities, inner regional Australia, outer regional Australia and remote (and very remote) Australia.

Some descriptive statistics are given in table 1. In particular, descriptive statistics by employment status shows differences in characteristics between unemployed and employed individuals. Weights are used as appropriate.

Measuring social contacts and neighborhood cohesion

In this study, independent variables about social contacts and neighborhood cohesion are derived from the answers to a set of ten questions as reported in Table 2. About neighborhood cohesion, the HILDA survey asks individuals whether neighbors help each other out, neighbors do things together, it is a close-knit neighborhood, people are willing to help neighbors, people in the neighborhood can be trusted and whether the individuals chat with their neighbors. About social contacts, the HILDA survey asks individual how often they get together socially with friends/relatives, whether they have a lot of friends, have contacts (telephone, email or mail) with friends/relatives and make time to keep in touch with friends.

This information is used to construct aggregate indicators of social contacts and perceived neighborhood cohesion by an individual for inclusion in our analysis. The former indicator gives information on the networks size and the intensity of the interactions for each individual, the latter indicator reflects the cohesion among individuals of a geographic area (neighborhood) where the individuals live. We use exploratory factor analysis as a dimension-reducing strategy to produce these indicators (which are assumed to be cardinal variables – see Ferrer-i-Carbonell and Frijters, 2004, for a justification for making this assumption). Factor analysis specifies the observed variables as linear combinations of the factors, plus normally distributed error terms. The algorithm produces a factor structure matrix (called the factor loading matrix) representing the correlations between the variables and the factors. See Table 2. The interpretation of each factor is informed by high loadings on a certain sub-sample of (related) attributes that assist in labelling the specific type of unobservable. Mean and standard deviation of the indicators are equal to zero and one, respectively, by construction.[9] Figure 1 shows the kernel estimates of the social contacts and the neighborhood cohesion density functions for our sample of young adults.

Measuring neighborhood deprivation

We use neighborhood deprivation as proxy of status of other individuals in the network since many social interactions happen locally. To define the level of neighborhood deprivation, we use the Socio-Economic Indexes for Areas (SEIFA) that ranks areas in Australia according to relative socio-economic advantage and disadvantage. The indexes reflect the socio-economic wellbeing of a geographic area. For each index, every geographic area in Australia is given a SEIFA score which measures how relatively 'advantaged' or 'disadvantaged' that area is compared with other areas in Australia. Each index summarizes a different aspect of the socio-economic conditions of people living in an area. We use the

[7] Regions are New South Wales, Victoria, Queensland, South Australia, Western Australia, Tasmania, Northern Territory and Australia Capital Territory.

[8] Note that we have information on neighborhood characteristics but cannot cluster by neighborhood since we do not have enough information in the data.

[9] Factor analysis is performed separately by each sample using the sample of all individuals aged [15,24] at t0, independently of their labor market status. We retain only factors which account for sufficient variance (Kaiser criterion) and we perform an oblique rotation, allowing factors to be correlated. Since factor analysis is based on a correlation matrix, it assumes that the observed variables are measured continuously, are distributed normally, and that the association between indicators is linear. Our observed variables are discrete, so we assume that they are indicators of underlying continuous unobserved variables and use the appropriate correlations in the factor analysis. The Kaiser–Meyer–Olkin measures of sampling adequacy is used to confirm that the variables have enough in common for the factor analysis to be valid.

Index of Education and Occupation that summarizes variables relating to the educational and occupational aspects of relative socio-economic disadvantage and the level of unemployment in the area.[10] We define a neighborhood as deprived by the decile of the Index, where a score equal to or below 4 represents deprivation.

3. Empirical results

In this section, we provide the main results of our models of the evolution of individual unemployment status over time. Table 3 carries a set of models that proceed from baseline by adding individual controls able to explain the individual probability of experiencing unemployment and persistence over time. The baseline is a dynamic binary choice model that includes variables about the network state (in terms of social contacts and neighborhood deprivation) and neighborhood cohesion as covariates. In a second variant of the model, past unemployment status is interacted with network state (in terms of social contacts and social contacts in deprived neighborhoods). We then test, in a third variant, whether neighborhood cohesion can mediate the impact of neighborhood deprivation on the individual probability of experiencing unemployment. Finally, in a forth variant, we test whether neighborhood cohesion has a different role according with the area's urbanization level (major cities versus areas with lower degree of urbanization). The last specification is the preferred specification on the basis of log-likelihood statistics though estimates appear to be relatively robust across the specifications.

After controlling for the unobserved effects, as expected, the coefficient on the lagged unemployment is highly statistically significant in any estimated specification. The initial value of labor market status (employed, unemployed or not in the labor market) is also very important, and it implies that there is substantial correlation between the initial condition and the unobserved heterogeneity, once again for any specification of the model. In fact, the coefficients on the variables describing the initial labor market status (unemployed; not in the labor market) are much larger than the coefficient on the lag unemployment for any specification of the model. Moreover, the estimate of the variance of the random intercept for individuals (σ_a^2) is positive and statistically significant. This means that there is large unobserved heterogeneity across individuals, even after explicitly controlling for the heterogeneity that we can observe by using socio-demographic characteristics.

Time constant socio-demographic characteristics included in any specification are gender, age, age squared, high education, immigration status, Aboriginal or Torres Strait Islander origin, region dummies and dummies about the urbanization level of the area where the individual lives. The time-varying individual variables included in any specification are: a) the number of adult household members; b) the marital status (or having a de facto partner); c) the presence of children in the household. Note that we include for each time-varying individual variable, the corresponding time-average variables (time-invariant variables) to allow for a correlation between the individual specific effects and the time-varying variables. Results show that high education significantly reduces the probability of experiencing unemployment. Females have lower probability of being unemployed than males (statistically significant only at 5% level), probably because only more qualified and/or more attached at the labor market females are in the labor market. The probability of experiencing unemployment is significantly higher for individuals with aboriginal or Torres Strait Islander origins. On the contrary, the estimated coefficient of the immigration variable is not statistically significant. The coefficients of age and its square are also not statistically significant. The coefficients of the mean number of adults in the household indicates that an increase in average number of adults in the household during the period reduces the probability

[10] The other indexes in SEIFA 2011 are: the Index of Relative Socio-economic Disadvantage that focuses on low income, low educational attainment, unemployment, and dwellings; the Index of Relative Socio-economic Advantage and Disadvantage that related to both advantage and disadvantage; the Index of Economic Resources that focuses on high and low income, as well as variables that correlate with high or low wealth. We perform robustness analysis using alternative SEIFA indexes and the main results are robust (results available upon request)

of experiencing unemployment. The adults in the household represent the closest individual network that provides both information on job opportunity and economic support during job search. Finally, individuals living in Tasmania, Queensland and the state of Victoria face a higher risk of unemployment (when compared to individuals living in the New South Wales).

Of most interest, we include the following variables in any specification: social contacts, neighborhood deprivation and social cohesion. Results show that social contacts significantly reduce the probability of experiencing unemployment. Since social contacts give information on the network size and the intensity of the interactions in the network, we find evidence that these factors increase the probability that information ends up in individual's hands and, therefore, reduce the probability of experiencing unemployment. Assuming that interactions happen mainly locally, the status of the members of the network can be associated with the level of neighborhood deprivation (that are neighborhoods with high unemployment). Results show that neighborhood deprivation significantly increases the probability of experiencing unemployment. A possible explanation is that the probability that information ends up in individual's hands is low if the percentage of unemployed in the neighborhood (network) is high. In principle, social cohesion can mediate the negative impact of deprivation on the risk of unemployment increasing the speed of spread of the information. In other words, we can assume that information spread faster if neighbors chat often and help each other (neighbors are willing to pass information about job opportunity to unemployed individuals as soon as possible). Our results support this idea (Model 3): we find neighborhood cohesion significantly reduces the probability of jobless in deprived neighborhood. In particular, the positive impact of neighborhood cohesion totally overcome the negative impact of neighborhood deprivation outside the major cities (Model 4).

Finally, our results show that the coefficient of the interaction between the lagged unemployment and social contacts is highly statistically significant in any estimated specification (Model 2, 3 and 4). Social contacts have, therefore, an impact on state dependence as discussed below in detail. The coefficients of the interaction across the lagged unemployment, social contacts and deprived neighborhood is positive according to the idea that individuals face relatively more competition for information in deprived neighborhoods, but it is not statistical significant.

True state dependence dynamics

We compute the magnitude of partial effects to analyze the relevance of state dependence on the probability to experience unemployment, conditional on the unemployment status in the previous period. We use the consistent estimator proposed by Wooldridge (2005):

(7) $$N^{-1}\sum_{i=1}^{N}\emptyset(z_{it}\,\gamma+\hat{\rho}_{1a}y_{t-1}(+\hat{\rho}_{2a}y_{t-1}network_{state_0})+\hat{a}_{0a}+\hat{a}_{1a}y_{i0}+z_i\hat{a}_{2a})$$

where the parameters are the estimated ones and the a subscript indicates a multiplication by $(1+\hat{\sigma}_a^2)^{-1/2}$.

Estimates of the probability of being unemployed in year t given that the individual is or is not unemployed in year t–1 are in Table 4. The difference is an estimate of the state dependence of being unemployed at time t. Both in model 1 and model 4, the probability to experience unemployment given that the individual was unemployed at t–1 is 0.21, and it decreases to 0.16 if the individual was employed at t–1. Thus, the estimate of the state dependence of unemployment is about 0.05. This means that, ceteris paribus, individuals experiencing unemployment in year t have a probability of being unemployed in year t+1 about 5% higher than those employed in year t. Thus, we can conclude that individuals participating in a certain network experiencing unemployment in a certain period have, ceteris paribus, a higher probability to experience unemployment in the future than employed individuals of that same network. Social contacts reduce this probability. Table 4 also presents the estimation of true state dependence assuming limited social contacts (defined as the 25th percentile): 0.06. It decreases to 0.38 assuming many social contacts (defined as the 75th percentile). Thus, a negative relationship between social contacts and the persistence in unemployment seems to emerge. However, social contacts seem to be less effective in deprived neighborhoods than they are in not-deprived neighborhoods: even if individuals have many social contacts, individuals experiencing unemployment in year t have a higher probability of being unemployed in year t+1 in deprived neighborhood (in our example, 5.1% vs 2.9%). This evidence seems to support the idea that the status of the members in the network matter: individuals face relatively more competition for information in deprived neighborhoods, probably because many members in the network are unemployed. Finally note that, as expected, neighborhood cohesion does not impact on state dependence (even if it reduces the risk of unemployment).

4. Conclusions

Using data from the Household Income and Labour Dynamics in Australia Survey, this paper considers individual unemployment risk and its relationship to the individual network of social contacts. We find that following empirical evidence. *First*, social contacts reduce both the unemployment risk and state dependence in unemployment. The disadvantage from having been unemployed in the previous period is high when the individual has limited social contacts and low when the individual has many social contacts. This is consistent with the idea that individuals obtain information about job opportunities through a network of social contacts and unemployment may lead to a decay of social capital, making it more difficult to find employment in future periods. *Second*, we point out that social contacts might be less effective in reducing unemployment persistence in deprived neighborhoods, that are high unemployment neighborhoods. Assuming that individual's contacts happen mainly locally in the neighborhood, a longer history of unemployment might be more likely to come when the direct and indirect connections of an individual are unemployed. In facts, the probability that information ends up in individual's hands is low if the percentage of unemployed connections in the network is high (individuals face relatively more competition for information). According to this, we find our *third* result: neighborhood deprivation increases the probability of experiencing unemployment. *Forth*, we find that neighborhood cohesion reduces the probability of jobless in deprived neighborhood and the positive impact of neighborhood cohesion totally overcome the negative impact of neighborhood deprivation outside the major cities. A possible explanation of the latter results is that social cohesion in the neighborhood affect the spread of information in the neighborhood: information spread faster if neighbors chat often and help each other.

Our results suggest that, given the persistence of individual unemployment risk and the role of social contacts related to the local context where the individual live and creates friendships, policies should devote more attention to the neighborhood dimension of unemployment. One implication is that it can be more efficient to concentrate subsidies or programs in specific neighborhoods so that a cluster of individuals who are interconnected in a network are targeted, rather than spreading resources more broadly. Another implication is about the importance to promote social cohesion in the deprived neighborhood thought community participation and events that permits people to meet and spread information about job opportunities.

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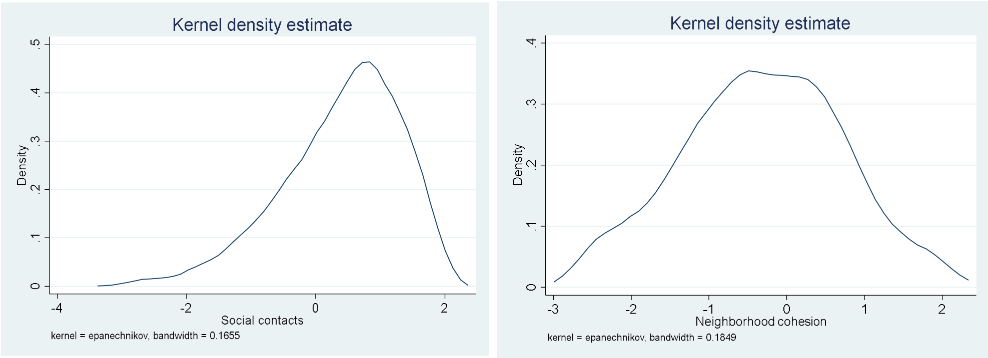
Figure 1. Kernel density estimate: social contacts and neighborhood cohesion



Note: individual in the labor market in the following three years only

Table 1. Descriptive Statistics (average from t=1 to t=3)

	All	Unempl.	Employed		All	Unempl.	Employed
Unemployed	5.91			area is NSW (%)	28.73	20.50	29.25
Age (mean)	21.78	20.67	21.85	area is VIC (%)	27.16	25.03	27.29
Female (%)	48.52	45.41	48.72	area is QLD (%)	19.49	28.58	18.92
High education (%)	16.68	5.73	17.37	area is SA (%)	7.44	8.03	7.41
Immigrant (%)	10.33	5.33	10.65	area is WA (%)	11.72	11.94	11.71
Aboriginal or Torres Strait Islander(%)	2.84	8.57	2.48	area is TAS (%)	2.15	4.64	1.99
Married (%)	6.10	1.44	6.39	area is NT (%)	0.76	0.74	0.76
No. adults in the household	3.01	2.98	3.01	area is ACT (%)	2.55	0.54	2.67
Children in the household (%)	19.42	24.08	19.13	Major City (%)	73.02	66.1	73.46
Deprived neighborhoods (%)	25.64	39.47	24.77	Inner Regional Australia (%)	19.04	26.73	18.56
Neighborhood cohesion (mean)	-0.328	-0.495	-0.317	Outer Regional Australia (%)	6.51	6.74	6.49
Social contacts (mean)	0.432	0.270	0.442	Remote Australia (%)	1.43	0.43	1.49
Employed at t=0 (%)	80.77	46.27	82.94	sample is 2006 (%)	29.15	21.62	29.68
Unemployed at t=0 (%)	6.65	22.64	5.65	sample is 2010 (%)	32.37	33.5	32.29
Not in the labor market at t=0 (%)	12.58	31.1	11.41	sample is 2014 (%)	38.48	44.88	38.03

Note: 3043 individuals (9,129 observations)

Table 2. Factor analysis

Questions	Scale	Rotated factor loadings (*)		
		2006	**2010**	**2014**
Neighborhood coehsion (factor 1)				
Neighbors helping each other out	1.Never happens-5.Very common	0.840	0.836	0.844
Neighbors doing things together	1.Never happens-5.Very common	0.785	0.778	0.784
This is a close-knit neighborhood	1-Strongly disagree -7.strongly agree	0.843	0.854	0.854
People around here are willing to help their neighbors	1-Strongly disagree -7.strongly agree	0.888	0.883	0.880
People in this neighborhood can be trusted	1-Strongly disagree -7.strongly agree	0.737	0.743	0.732
Chat with your neighbors	1-never -6. Very often	0.639	0.637	0.651
Social contacts (factor 2)				
How often get together socially with friends/relatives not living with you	1.every day – 7.less than once every 3 months	- 0.675	-0.686	-0.687
I seem to have a lot of friends	1-Strongly disagree -7.strongly agree	0.671	0.677	0.685
Have telephone, email or mail contact with friends /relatives not living with you	1-never -6. Very often	0.724	0.718	0.701
Make time to keep in touch with friends	1-never -6. Very often	0.835	0.834	0.837
Kaiser-Meyer-Olkin measure of sampling adequacy		0.834	0.841	0.838

(*) we report only if abs(loading)<.4

Table 3. Estimates

Dependent variable is unemployed at t	Model 1			Model 2			Model 3			Model 4		
	Coef		SE	Coef		SE	Coef		SE	Coef		SE
employed at t0	ref			ref			ref			ref		
unemployed at t0	1.002	**	0.146	0.994	**	0.146	0.991	**	0.146	0.989	**	0.145
not in labour market at t0	0.885	**	0.102	0.879	**	0.101	0.876	**	0.101	0.876	**	0.101
unemployed at t-1	0.473	**	0.114	0.514	**	0.115	0.515	**	0.115	0.514	**	0.115
unemp(t-1)*social contacts				-0.205	**	0.064	-0.205	**	0.064	-0.205	**	0.062
unemp(t-1)*s. contacts*deprived n.				0.127		0.136	0.137		0.136	0.141		0.136
Age	-0.191		0.159	-0.193		0.159	-0.188		0.158	-0.188		0.158
age*age	0.004		0.004	0.004		0.004	0.004		0.004	0.004		0.004
Female	-0.145	*	0.067	-0.150	*	0.067	-0.148	*	0.067	-0.147	*	0.067
high education	-0.358	**	0.130	-0.360	**	0.129	-0.361	**	0.129	-0.361	**	0.129
Immigrant	-0.213		0.154	-0.218		0.155	-0.213		0.154	-0.216		0.154
aboriginal or Torres Strait Islander	0.443	**	0.157	0.431	**	0.157	0.424	**	0.156	0.422	**	0.156
Married	-0.022		0.370	-0.023		0.370	-0.023		0.370	-0.026		0.371
No. adults in the household	0.065		0.041	0.065		0.041	0.065		0.041	0.064		0.041
Children in the household	-0.027		0.133	-0.023		0.133	-0.018		0.134	-0.017		0.134
Social contacts	-0.117	**	0.037	-0.093	**	0.033	-0.092	**	0.032	-0.093	**	0.032
deprived neighbour (sed<=4)	0.220	**	0.072	0.214	**	0.072	0.215	**	0.072	0.205	**	0.072
deprived*n. cohesion							-0.234	**	0.079			
deprived*n. cohesion*(hhra>=2)										-0.312	**	0.115
neighbours cohesion	-0.065	*	0.033	-0.065	*	0.033	-0.044		0.034	-0.047		0.034
period and sample dummies	yes			yes			yes			yes		
area is NSW	ref			ref			ref			ref		
area is VIC	0.194	*	0.095	0.192	*	0.095	0.194	*	0.095	0.193	*	0.095
area is QLD	0.324	**	0.094	0.318	**	0.094	0.324	**	0.094	0.328	**	0.094
area is SA	0.131		0.123	0.133		0.123	0.142		0.123	0.140		0.123
area is WA	0.179		0.131	0.182		0.131	0.183		0.130	0.183		0.130
area is TAS	0.513	**	0.182	0.526	**	0.181	0.524	**	0.180	0.518	**	0.180
area is NT	0.120		0.415	0.115		0.414	0.065		0.424	0.060		0.424
area is ACT	-0.367		0.288	-0.361		0.287	-0.355		0.286	-0.359		0.286
Major City (hhra=1)	ref			ref			ref			ref		
Inner Regional Australia (hhra=2)	-0.067		0.082	-0.064		0.082	-0.060		0.081	-0.058		0.081
Outer Regional Australia (hhra=3)	-0.181		0.124	-0.179		0.124	-0.276	*	0.136	-0.289	*	0.136
Remote Australia (hhra=4)	-0.388		0.295	-0.381		0.293	-0.401		0.298	-0.407		0.297
mean_married	-0.683		0.408	-0.669		0.407	-0.676		0.407	-0.685		0.408
mean_hhadult	-0.122	*	0.052	-0.121	*	0.051	-0.120	*	0.051	-0.122	*	0.051
mean_children	0.096		0.163	0.089		0.163	0.082		0.163	0.085		0.163
Constant	0.069		1.695	0.093		1.691	0.047		1.688	0.066		1.688
$\hat{\sigma}_a$	0.793	**	0.094	0.788	**	0.094	0.782	**	0.094	0.781	**	0.094
$\hat{\sigma}_a / (\hat{\sigma}_a + \hat{\sigma}_\varepsilon)$	0.386	**	0.056	0.383	**	0.056	0.379	**	0.057	0.379	**	0.057
.	-1745.644			-1743.529			-1741.18			-1740.59		
No. Obs	9,129			9,129			9,129			9,129		
No. Individuals	3043			3043			3043			3043		

Note: (**) and (*) statistical significant, respectively, at 1% and 5% level.

Table 4. State dependence

Dynamic probit model	unemp(t-1) = 1	Unemp(t-1) = 0	State dependence
Probability (Model 1)	0.210	0.157	0.053
Probability (Model 4)	0.207	0.156	0.051
Probability (model 4)…			
Assuming many social contacts	***0.187***	***0.150***	***0.038***
and deprived neighborhood	0.213	0.162	0.051
and high neighborhood cohesion	0.206	0.156	0.050
and low neighborhood cohesion	0.221	0.168	0.053
and not deprived neighborhood	0.170	0.141	0.029
Assuming limited social contacts	***0.224***	***0.161***	***0.063***
and deprived neighborhood	0.239	0.174	0.065
and high neighborhood cohesion	0.231	0.168	0.063
and low neighborhood cohesion	0.247	0.181	0.066
and not deprived neighborhood	0.213	0.152	0.061

Note: limited social contacts = -.1480883 (25th percentile); many social contacts= 1.096158 (75th percentile)