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# Labour Market Outcomes and the Impacts of Social Networks: Evidence from the Cape Town Metropolitan Area

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## Abstract

This paper examines whether social networks have an effect on the decision to participate in the labour market by individuals in the greater Cape Town area. By using the fourth wave of the Cape Area Panel Study (CAPS) this paper empirically confirms previously examined results of a network effect for employment prospects while confirming that no network effect is present for labour discouragement. The results indicate that a network effect increases the impact of employment orientated policies by between 1.7 and 13%. The econometric approach adopted in this paper minimises omitted variable bias which would incorrectly overstate the presence of the network effect in the results. The finding that there is no network effect on discouragement from the members of an individual's broader friendship network indicates that labour discouragement is largely influenced by various unexplored psychological aspects.

## Introduction

Information transfers, social pressures, and the transmission of norms and values through social networks has only recently become of interest to economists (Bertrand, Luttmer and Mullainathan 2000). Social networks allow for very complex interactions to take place between individuals and therefore have very important implications for their collective behaviours (Burns, Godlonton and Keswell 2010). Despite the limited research that has been done on social networks, it has been shown that networks have pronounced effects on the educational attainment, and welfare procurement of an individual as well as the likelihood that an individual will participate in criminal activities (Bertrand *et al* 2000, Case and Katz 1991). In the labour market, social networks are known to affect employment prospects of individuals as the incidence of employment in a social network provide individuals with different qualities of information spillovers about job prospects and appropriate methods of employment search (Burns *et al* 2010; Ioannides and Loury, 2004). Despite previous studies looking at social network effects in the labour market, previous work on such effects on labour discouragement is generally lacking.

Table 1 summarises some of the previous work done on social networks and its effects on the outcomes of individuals. It indicates the importance of social networks in economic theory and also illustrates various methods of selecting a social network.

This paper examines the impact of networks on labour market outcomes, namely the likelihood that an individual will be employed, unemployed or discouraged given the characteristics of their network. A positive social network effect on employment would result in a magnification of employment policies. That is, as more people are finding work their employment status would positively influence those unemployed individuals in their social circles. If social networks influence discouragement, on the other hand, they could result in a form of self-reinforcing equilibrium. This equilibrium would be the product of individuals refraining from the job search due to the high incidence of discouragement in the network, while this incidence would be reinforced by the discouraged members. If this effect is present, then communities that are almost completely discouraged would exist. Any job vacancies or job creation programs would not be occupied by these discouraged networks entirely and thus will result in labour mobility rigidities. A lack of workforce in communities would require policy shocks to encourage labour participation. Labour discouragement is a drain on the national fiscus, due to a sub-optimal match between individuals and employment. Attempts should, thus, be made to limit its prevalence. In South Africa, with a narrow unemployment rate (excluding discouraged individuals) of around 25%

(StatsSA 2011) and a broad unemployment rate of around 37%, policies should be implemented which entice discouraged individuals back into the job market.

The identification and measurement of social networks greatly influences the results of previous social network studies (Conley and Udry, 2008), for this reason the choice of what social network to use must be done with care. A social network, ideally, would be measured by actual contacts. This data however, is seldom available (Conley and Udry, 2008: 3) and when present it does have omitted variable characteristics, due to a self-selection effect, that can influence empirical results. The methods for identifying a social network vary between studies and it shows that networks have various positive effects on personal outcomes. Not only is the identification of contacts available to individuals important, an understanding of the amount certain contacts influence an individual is also vital. The strength, or impact, of interpersonal ties depends, according to Granovetter (1974: 1361), on the amount of time, the intensity and the intimacy of interactions between individuals. Thus, this paper will consider the ties between individuals in a common household to be stronger than those between individuals with some minimal interaction. In this paper, weak ties will be sparse interactions between individuals in a neighbourhood while strong ties will the interactions between individuals who live in a common household. The primary focus in this paper is the weak ties due to their broad impact on mobility rigidities.

**Table 1: Previous Empirical Work Dealing with Social Networks**

| Author | Study | Network | Findings |
|---|---|---|---|
| Bertrand, Luttmer and Mullainathan (2000) | Network effects and welfare attainment | Common language speakers in a defined neighbourhood | An increase in welfare procurement in an individual's language group increases the likelihood of taking up welfare. |
| Burns, Godlonton and Keswell (2010) | Social Networks and employment and discouragement levels | Age-Language cohorts in common magisterial districts | Social networks positively affect employment levels indirectly by between 3 and 12% while they do not affect discouragement levels. |
| Case and Katz (1991) | Effect of family and neighbourhood peers on the behaviour of youths | Mean incidence of individuals in the common neighbourhood and family | The actions of family members have a substantial positive affect the behaviours and outcomes of youths |
| Conley and Udry (2008) | Transfer of technology between pineapple farmers | Actual contact data on who individuals talk to about farming | Farmers tend to increase the number of farming inputs if their networks reap positive results with additional inputs. |
| Datcher (1982) | Family background and community on education and earnings of men aged 23 - 32 | Mean incidence of individuals in the common neighbourhood and family | Neighbourhood quality positively affects earnings and educational attainment |
| Sacerdote (2001) | Peer effects with random assignment on academic results | Roommates and members of a common dorm | The quality of peers affects academic outcomes. Having top performers in one's network positively increases academic results. |
| Zimmerman (2003) | Peer effects and Academic Outcomes | Roommates and members of common boarding environments | Peer groups affect academic results in both positive and negative ways given the performance of the individual prior to the network interaction. |

By following the strategy set out by Bertrand *et al* (2000), which minimises omitted variable bias by including various fixed effects, this paper evaluates whether social networks have an effect on labour market outcomes; namely whether an individual is employed, unemployed or discouraged. While the network of primary interest is the weaker, friendship, networks of individuals, the effect of stronger, household, network ties will also be explored. As data on the exact network interactions of individuals is lacking, this paper will proxy the social networks by age-neighbourhood cohorts. In essence it is assumed that individuals of a similar age who live in the same area will have a degree of weak interaction. This proxy is similar to the language proxy used by Bertrand *et al* (2000) and the age-language proxy used by Burns *et al* (2010).

The findings of this paper confirm the results presented in Burns *et al* (2010) that there is a significant network effect with regard to employment and unemployment in South Africa. Labour discouragement, however, does not seem to be influenced by weaker social networks as no significant results are present when omitted variable bias is accounted for. The effects of social networks on discouragement are therefore explored further and the results indicate that strong ties appear to have some effect on discouragement. This suggests that, while individuals rely on a combination of strong and weak ties for employment possibilities, the refraining from active job search is only affected by stronger, in-house, ties.

## Methodology

The probability that an individual is employed is given by the following model.

$$\Pr(EMPL_{ijk}) = Netw_{ijk}\alpha^* + X_i^*\beta^* + Y_j^*\gamma^* + Z_k^*\delta^* + \varepsilon_{ijk}$$

Here *i* indexed individuals, *j* neighbourhoods, and *k* indexes the age cohorts. The employment measure, $EMPL_{ijk}$, takes the form of a dummy variable showing a unit value if the individual is employed and zero otherwise. The Network measure, *Netw,* describes the effect of social pressures and information spillovers on an individual pertaining to employment prospects. $X_i^*$ and $Y_j^*$ are observed and unobserved personal and area characteristics respectively, while $Z_k^*$ relates to observable and unobservable age cohort characteristics.

While information on an individual's actual social network would be best, at mentioned previously, it is not generally available. Thus the network variable, $Netw_{ikj}$, needs to be estimated through the use of proxy variables. Direct use of mean neighbourhood statistics has been frequently used, incorrectly. Such a method assumes that individuals are randomly distributed within neighbourhoods (Burns *et al* 2010). This assumption is clearly inappropriate as individuals tend to, at least partly; self-select their social networks and the environment they live in.

Despite findings suggesting correlations between individual outcomes and mean neighbourhood statistics, the casual use of a mean neighbourhood proxy would not account for the possible presence of omitted variable bias (Burns *et al* 2010). Such a bias would be the result of unobservable personal and neighbourhood characteristics which may correlate with the incidence of employment. A personal unobservable variable may consist of, for example, individuals who show an innate tendency to be proactive may self-select a certain neighbourhood with a high incidence of employment. An omitted neighbourhood variable could be the location of the neighbourhood. Rural areas, for example, may have so few job openings which would make the employment opportunities minimal.

A social network is made up by both quality and quantity dimensions. The quantity of one's contact pool interacts with the incidence of employment, or quality, of the social network members. The method used to proxy for social networks in this paper assumes that individuals of a similar age, living in a defined common neighbourhood will have some degree of social contact. In order to effectively use this proxy, the network measure must relate to the number of people an individual interacts with combined with the collective views, attitudes and information those individuals have to offer (Bertrand *et al* 2000). Zimmerman (2003), for example, proxies the academic social network by those individuals who lived in a common space in academic housings. The number of contacts available $(C_{jk})$ to an individual is therefore multiplied by the quality, or mean incidence of employment $(\overline{EMPL}_k)$, of the members of the common age-neighbourhood cohort. The network measure is therefore given as $Netw_{ijk} = (C_{JK} \times \overline{EMPL}_k)$.

Calculating the quantity of contacts available by means of a simple proportionate measure of the number of people in a neighbourhood belonging to an age cohort would be inappropriate for a study like this. Such a measure would overweight small age-populations who may self-select a neighbourhood. Such a case would be neighbourhoods with a high population of individuals between 56-65 years of age. Instead the method set out by Bertrand *et al* (2000: 1029) is used to measure contact availability. This method takes the natural log of the number of individuals of the same age cohort in a neighbourhood $(P_{jk})$ divided by the population of the neighbourhood $A_j$, which is divided by the total number of the relevant age cohort in the data set $(L_k)$ over the entire recorded population $(T)$. This is depicted as follows:

$$C_{jk} = In \frac{P_{jk}/A_j}{L_k/T}$$

Given the network definition above, the estimation equation for the network effect on employment is given by:

$$EMPL_{ijk} = \left(C_{jk} \times \overline{EMPL_k}\right)\alpha + X_i b + g_j + d_k + C_{jk} f + e_{ijk}$$

Fixed effects for neighbourhoods $(g_j)$ and age cohorts $(d_k)$ are included to minimise any unobservable variable bias that may be correlated with employment. The interaction of $C_{JK}$ and $\overline{EMPL_k}$ is, as mentioned above, the network measure. $C_{jk}$ is, in addition, included as its own control as it deals with omitted variable bias that may arise from a possible correlation between individuals who choose to live in a neighbourhood with more people their age. $\overline{EMPL_k}$ is not included in a similar manner as any omitted variable correlated with employment that may be present is included in $d_k$. $e_{ijk}$ is the error term and $b$ is the coefficient for personal characteristics which could impact employment. The element of interest is the $\alpha$ term. A significant $\alpha$ value indicates that network effects are present in the data.

The inclusion of fixed effects makes logit or probit estimation of this model computationally difficult, thus a linear probability model is used despite the binary nature of the dependent variable.

## Data

The fourth wave (2006) of Cape Area Panel Study (CAPS) data is used to model the given estimation equation. This data set looks at individuals in the Cape Town metropolitan area. The fourth wave focuses on the youths and young adults interviewed in the first wave (2002) and the members of their households. The sample, therefore, over represents the proportion of younger individuals (almost 40% of the individuals in sample are between the ages of 18 and 25). This disproportionately high young population would affect the mean age related statistics by some measure; but it should not have an effect on the network regression statistics as the networks are distinguished by age cohort.

With the focus being on those individuals suitable for the labour market, the regressions and mean statistics from the sample was limited to individuals aged between 18 and 65. Individuals at school, or who were not eligible for work were excluded from the regressions. Out of the sample 52% were employed, leaving 48% of the population unemployed according to the broad definition.

Out of the unemployed population (not working for monetary or household gain) 84% of them had refrained from looking for work in the week prior to their interview. Out of the individuals who have indicated that they have not looked for work in the past week, 42% of them indicated that they would like work[1].

Table 2 presents summary statistics for the sample by employment, unemployment and discouragement statuses.



[1] StatsSA (2011) estimates discouraged unemployment to be around 34%. They define a discouraged individual as being one who is not employed, willing to work, but did not look for employment in the previous four weeks. The main reasons cited by StatsSA (2011: xvii) for in individual to become discouraged are “no jobs available in the area; unable to find work requiring his/her skills; lost hope of finding any kind of work.”

**Table 2: Mean Statistics for the Sample by Employment Status**

| Variable | All | | Employed Individuals | | Unemployed Individuals | | Discouraged Individuals | |
|---|---|---|---|---|---|---|---|---|
| Individual is Black | 0.435 | (0.49) | 0.371 | (0.48) | 0.505 | (0.50) | 0.483 | (0.50) |
| Individual is Coloured | 0.49 | (0.49) | 0.533 | (0.50) | 0.443 | (0.50) | 0.458 | (0.50) |
| Individual is White | 0.071 | (0.26) | 0.091 | (0.29) | 0.049 | (0.22) | 0.056 | (0.23) |
| Individual is Indian | 0.003 | (0.06) | 0.004 | (0.06) | 0.003 | (0.05) | 0.003 | (0.06) |
| Age | 34.76 | (13.92) | 36.14 | (12.81) | 33.25 | (14.89) | 31.19 | (20.31) |
| Age Bracket 1: 18 - 25 | 0.399 | (0.49) | 0.317 | (0.47) | 0.488 | (0.50) | 0.476 | (0.50) |
| Age Bracket 2: 26 - 35 | 0.17 | (0.38) | 0.198 | (0.40) | 0.139 | (0.35) | 0.124 | (0.33) |
| Age Bracket 3: 36 - 45 | 0.155 | (0.36) | 0.193 | (0.40) | 0.113 | (0.32) | 0.112 | (0.32) |
| Age Bracket 4: 45 - 55 | 0.177 | (0.38) | 0.213 | (0.41) | 0.138 | (0.34) | 0.147 | (0.35) |
| Age Bracket 5: 56 - 65 | 0.1 | (0.29) | 0.079 | (0.27) | 0.122 | (0.33) | 0.141 | (0.35) |
| Individual has a Matric | 0.298 | (0.46) | 0.366 | (0.48) | 0.223 | (0.42) | 0.214 | (0.41) |
| Years of Education | 8.872 | (3.09) | 9.986 | (3.05) | 9.017 | (3.05) | 8.922 | (3.08) |
| The Individual is a Male | 0.453 | (0.49) | 0.516 | (0.50) | 0.384 | (0.49) | 0.367 | (0.48) |
| The Individual is Married | 0.342 | (0.47) | 0.413 | (0.49) | 0.265 | (0.44) | 0.277 | (0.45) |
| Households with Children Under the Age of 6 present | 0.014 | (0.14) | 0.011 | (0.11) | 0.016 | (0.16) | 0.016 | (0.16) |
| Fraction of Employed individuals in the House hold (Not Including Individual) | 0.374 | (0.24) | 0.386 | (0.24) | 0.362 | (0.23) | 0.367 | (0.23) |
| Age Bracket 1: 18 - 25 | 0.4 | (0.23) | 0.424 | (0.23) | 0.383 | (0.23) | 0.388 | (0.22) |
| Age Bracket 2: 26 - 35 | 0.363 | (0.23) | 0.386 | (0.24) | 0.325 | (0.22) | 0.33 | (0.22) |
| Age Bracket 3: 36 - 45 | 0.357 | (0.23) | 0.365 | (0.24) | 0.342 | (0.22) | 0.355 | (0.22) |
| Age Bracket 4: 45 - 55 | 0.37 | (0.24) | 0.366 | (0.25) | 0.377 | (0.24) | 0.379 | (0.24) |
| Age Bracket 5: 56 - 65 | 0.329 | (0.25) | 0.337 | (0.25) | 0.323 | (0.25) | 0.324 | (0.25) |

*Notes:*
Data Source: Cape Area Panel Study
Wave 4 (2006)
"Unemployed Individuals" Includes Discouraged Individuals
Figures In Brackets Are Standard Deviations
Rows Sum To One

Focusing on racial distributions in this sample, it is apparent that black individuals are over represented among the unemployed and underrepresented among the employed relative to their overall population. This racial disparity is evident as black individual's makeup 43.5% of the sample while only accounting for 37.1% of the employed. The other three measured races have converse statistics; coloured, white and indian individuals are all over represented in the employed population relative to their share in the sample. White individuals, for instance, make up 7.1% of the sample while accounting for 9.1% of the employed.

Pertinent to the network study is the potential access to job information from members of a household through strong ties. Employed individuals tend to live in households where 38.6% of age appropriate individuals, excluding the primary individual, are employed while unemployed individuals live in households with a slightly smaller percentage of working adults. This measure is used later when assessing whether strong in-house ties have an effect on employment.

Employment incidence is higher for men than for women as 51.6% of men are employed while they only make up 45.3% of the sample. In addition, women appear to be more prone to discouragement than men, as shown by the smaller percentage (36.7) of discouraged men compared to their proportion among the unemployed (38.4). Individuals with a matric appear to enjoy employment more readily than those without as 36.6% of the individuals with a matric are employed despite only 29.8% of the individuals have this qualification. A child under the age of 6 is more likely to be found in a household with an unemployed individual than an employed one as 1.6% of unemployed individuals has a child under the age of 6 in their household compared to 1.1% of the employed.

Table 3 presents mean statistics for employment, unemployment and discouragement based on race, gender, age and education. It presents the probability that an individual of a certain race or age bracket drawn from the sample will be employed, unemployed or discouraged. The results give similar interpretations to those in table 2 with more unemployed (55.5%) than employed (45.5%) black individual's showing converse results to the higher employment probability for white, coloured and indian individuals. While indian individuals appear to be the most likely to become discouraged, their population is so small in this sample it should not be taken definitively. Black individuals, as shown above, are the least likely to become discouraged compared to the other racial groups. The statistics for individuals in age bracket 4, 45 – 55 year olds, is interesting. This age bracket has a relatively modest unemployment rate (37.2%), but a very high discouragement rate among those unemployed individuals.

**Table 3:Mean Statistics for Age, Race, Gender and Education**

| Variable | Employed | | Unemployed | | Discouraged | |
|---|---|---|---|---|---|---|
| Black | 0.445 | (0.49) | 0.555 | (0.50) | 0.810 | (0.39) |
| White | 0.669 | (0.47) | 0.331 | (0.47) | 0.970 | (0.17) |
| Coloured | 0.568 | (0.50) | 0.432 | (0.50) | 0.871 | (0.33) |
| Indian | 0.588 | (0.49) | 0.412 | (0.50) | 1 | (0) |
| Age Bracket 1: 18 - 25 | 0.415 | (0.49) | 0.585 | (0.49) | 0.824 | (0.38) |
| Age Bracket 2: 26 - 35 | 0.608 | (0.49) | 0.392 | (0.49) | 0.757 | (0.43) |
| Age Bracket 3: 36 - 45 | 0.651 | (0.48) | 0.349 | (0.48) | 0.838 | (0.37) |
| Age Bracket 4: 45 - 55 | 0.628 | (0.48) | 0.372 | (0.48) | 0.905 | (0.29) |
| Age Bracket 5: 56 - 65 | 0.414 | (0.49) | 0.586 | (0.49) | 0.976 | (0.15) |
| Individual Has a Matric | 0.641 | (0.48) | 0.359 | (0.48) | 0.809 | (0.39) |
| Individual is Male | 0.595 | (0.49) | 0.405 | (0.49) | 0.808 | (0.39) |

*Notes:*

Data Source: Cape Area Panel Study Wave 4

Figures in Brackets are standard deviations

Sums to 1 across columns

Indian only has 34 observations



## Regression Results

The estimation equation $EMPL_{ijk} = \left(C_{JK} \times \overline{EMPL}_k\right)\alpha + X_i b + g_j + d_k + C_{jk} f + e_{ijk}$ is regressed and the results are given in table 4 below. The first two sets of regressions consider employment and unemployment while the third set of regressions considers discouragement relative to the mean incidence of employed individuals in the neighbourhood ($EMPL_{ijk} = \left(C_{JK} \times \overline{DISC}_k\right)\alpha + X_i b + g_j + d_k + C_{jk} f + e_{ijk}$). For each set of regressions, the first regression has no fixed effects included, the second has fixed effects accounting for age $(d_k)$ included and the third regression contains both age $(d_k)$ and neighbourhood $(g_j)$ fixed effects. It is worth noting that there were 440 neighbourhoods in the sample which were defined by geographic location and were distributed throughout the greater Cape Town metropolitan area.

Considering the employment and unemployment regressions there is a large decline in the network effect $(\alpha)$ when the fixed effects are included in each model. For the employment regression, the network coefficient falls substantially from 1.035 when there are no controls, to 0.573 when controls are introduced. During this decline the network coefficients remain significant at the one percentage level when no controls are included and significant at the five percentage level when controls are included. Similar results are present when the converse, the effect of social networks on unemployment, is tested. There is a mirror image of the network effect on employment when unemployment is regressed given a mean incidence of employment. This statistic ranges from -1.035 when there are no fixed effects to -0.573 when fixed effects are included for age and neighbourhood. The statistics remain significant despite the addition of the fixed effects. This loss of impact and significance of a network effect on employment and unemployment when fixed effects are included indicates that a failure to include fixed effects would have resulted in an over estimation of the relevant network effects for these regressions.



**Table 4: Regression Estimates of Network Coefficients as Additional Fixed Effects are Included**

| | Probability Individual is Employed | | | Probability Individual is Unemployed | | | Probability unemployed Individual is Discouraged | | |
|---|---|---|---|---|---|---|---|---|---|
| | -1 | -2 | -3 | -1 | -2 | -3 | -1 | -2 | -3 |
| Contact Availability | -0.146* | -0.089 | -0.142* | 0.146* | 0.891 | 0.142* | 0.012 | 0.035 | 0.083 |
| | (0.048) | (0.041) | (0.041) | (0.480) | (0.339) | (0.041) | (0.039) | (0.398) | (0.059) |
| Network Effect | 1.035** | 0.609** | 0.573* | -1.035** | -0.609** | -0.573* | -0.108 | -0.055 | -0.327 |
| | (0.229) | (0.196) | (0.2) | (0.229) | (0.166) | (0.2) | (0.184) | (0.187) | (0.284) |
| Constant | 0.516** | 0.642** | 0.653** | 0.483** | 0.357** | 0.35** | 0.843** | 0.835** | 0.841** |
| | (0.007) | (0.014) | (0.011) | (0.007) | (0.012) | (0.012) | (0.008) | (0.019) | (0.017) |
| Observations | 10217 | 10217 | 10217 | 10217 | 10217 | 10217 | 4847 | 4847 | 4847 |
| R-squared | 0.005 | 0.05 | 0.11 | 0.005 | 0.05 | 0.11 | 0.001 | 0.03 | 0.14 |
| Age Fixed Effects | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Neighbourhood Fixed Effects | NO | NO | YES | NO | NO | YES | NO | NO | YES |

*Notes:*
Data Source: Cape Area Panel Study Wave 4
* Significant at 5% level; ** Significant at 1% Level
Robust Standard Errors in Parentheses

The third set of regressions looks at the network effect on discouragement given the mean incidence of employment in the network. Even prior to the inclusion of fixed effects, the results do not show a significant network effect. Since this coefficient is very close to zero and insignificant, it indicates that there is no network effect for discouragement. That is, an increase in the number of employed individuals in an individual's weak social network does not influence discouragement.

## Interpreting the Network Effect Coefficient

Interpreting the coefficient value of a network effect is complicated due to the manner it is derived. To interpret the network effect of 0.573 on employment found when fixed effects are included in table 4, the method set out by Bertrand *et al* (2000) is used. This method considers a policy ($\psi$) which affects employment with linear impact. This policy is then included in the estimation model and scaled such that a percentage point increase in $\psi$ results in a percentage point increase in employment when no network effect is present. In other words the model looks as follows: $EMPL_{ijk} = \psi + \left(C_{jk} \times \overline{EMPL_k}\right)\alpha + X_i b + g_j + d_k + C_{jk} f + e_{ijk}$.

The positive network effect coefficient indicates that the increase in employment will be greater than the initial policy effect $\psi$. By averaging both sides of the equation for each age cohort, differentiating with respect to $\psi$, and solving, one generates a measure of responsiveness of each age cohort when faced with a policy shock. This measure is given by $\frac{1}{(1-\alpha\overline{C_K})} - 1$, where $\overline{C_K}$ is the mean of $C_{JK}$ in each age cohort.

With the given alpha (α) value of 0.573 and the relevant mean contact availability measures, the following indirect effects of social networks were generated.

**Table 5: Indirect Network Effects on Employment Probabilities**

| Age Bracket | α | $\overline{C_k}$ | **Indirect Effect** | |
|---|---|---|---|---|
| All | 0.573 | 0.102 | 0.062 | (0.02) |
| Age Bracket 1: 18 - 25 | 0.573 | 0.028 | 0.017 | (0.01) |
| Age Bracket 2: 26 - 35 | 0.573 | 0.155 | 0.098 | (0.03) |
| Age Bracket 3: 36 - 45 | 0.573 | 0.144 | 0.089 | (0.02) |
| Age Bracket 4: 45 - 55 | 0.573 | 0.124 | 0.077 | (0.02) |
| Age Bracket 5: 56 - 65 | 0.573 | 0.202 | 0.131 | (0.03) |

*Notes:*
Data Source:Cape Area Panel Study Wave 4
Figures in Brackets are Standard Deviations
Standard deviations calculated using the delta method

These results indicate that social networks enhance employment prospects for individuals generated through policy shocks on average around 6%. Policies enhancing employment prospects for individuals between the ages of 18 and 25 are magnified by 1.7 % while for older individuals between the ages 56 and 65 this magnification is around 13.1 %.

## How Robust is the Network Effect?

Table 6 below presents regression estimates which include additional controls for personal characteristics of the individuals and their households. The additional controls included race and education for the first regression and the fraction of employed individuals in the household for the second. Focusing on employment, the inclusion of the additional controls, result in a further decline in the network effect to 0.468. This estimate becomes statistically insignificant (significant at the 14% level). In column 2 an additional control for the fraction of employed individuals in the household, or probability of employment based on household results, is included. An increase in the number of employed individuals, of working age, in the household significantly increases an individual's employment prospects. This measure is regarded as a measure for the effect of the strong ties on the individuals. This result is slightly different from the result generated by Burns *et al* (2010). Their network effect coefficient ($\alpha$) remained significant when personal characteristics and the fraction of working individuals in the household were included in the regression.

Column 3 and 4 continue to show an insignificant network effect for discouragement. This confirms the results in table 4 that weaker ties do not have a network effect on discouragement. The included fraction of employed individuals in the household coefficient (in column 4) was not significant suggesting that employed family members do not affect discouragement decisions.

**Table 6: Regression Estimates of Network Coefficients Including Additional Controls**

| | Probability Individual is Employed | | Probability Individual is Discouraged | |
|---|---|---|---|---|
| | -1 | -2 | -3 | -4 |
| Contact Availability | -0.131* | -0.130* | 0.076 | 0.076 |
| | (0.038) | (0.037) | (0.059) | (0.059) |
| Network Effect | 0.471 | 0.468 | -0.28 | -0.282 |
| | (0.19) | (0.189) | (0.283) | (0.286) |
| Individual is Black | -0.057 | -0.062 | 0.105 | 0.107 |
| | (0.068) | (0.071) | (0.096) | (0.096) |
| Individual is Coloured | -0.01 | -0.012 | -0.054 | -0.055 |
| | (0.047) | (0.049) | (0.063) | (0.063) |
| Individual is Indian | -0.008 | -0.008 | 0.047 | 0.046 |
| | (0.086) | (0.091) | (0.061) | (0.062) |
| Individual has a matric | 0.038 | 0.038 | -0.03 | -0.03 |
| | (0.017) | (0.017) | (0.023) | (0.023) |
| Years of Education | -0.01 | -0.009 | -0.003 | -0.003 |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Years of Education Squared | 0.002** | 0.002** | -0.001 | -0.002 |
| | (0) | (0) | (0) | (0) |
| Fraction of Employed individuals in the Household | | 0.078* | | 0.025 |
| | | (0.029) | | (0.032) |
| Constant | -1.31** | -1.27** | 1.37** | 1.36** |
| | (0.986) | (0.102) | (0.119) | (0.12) |
| Observations | 10217 | 10217 | 4847 | 4847 |
| R-squared | 0.17 | 0.17 | 0.15 | 0.16 |

Robust Standard Errors in Parentheses
* Significant at 5% Level; ** Significant at 1% Level
Includes Fixed Effects for Age and Neighbourhoods



## The Effect of Strong Ties on Discouragement

As shown previously, there does not appear to be any significant effect of an individual's weaker social network on the presence in the labour market. To assess whether discouraged family members could have any effect on the discouragement decision, a set of estimates like those given in table 6 are generated. This regression assesses whether the fraction of individuals (of working age) in the household who are discouraged has an effect on labour discouragement. If the strong ties have an effect on discouragement then one would expect a significant relationship with this control and the probability that one is discouraged. The estimated results are given in table 7.

**Table 7: The effect of Strong Ties on Discouragement**

| | **Probability Unemployed Individual is Discouraged** | |
|---|---|---|
| | -1 | -2 |
| Contact Availability | 0.076 | 0.082 |
| | (0.059) | (0.059) |
| Network Effect | -0.280 | -0.296 |
| | (0.283) | (0.282) |
| Individual is Black | 0.105 | 0.094 |
| | (0.096) | (0.093) |
| Individual is Coloured | -0.054 | -0.059 |
| | (0.063) | (0.063) |
| Individual is Indian | 0.047 | 0.034 |
| | (0.061) | (0.063) |
| Individual has a matric | -0.029 | -0.031 |
| | (0.023) | (0.022) |
| Years of Education | -0.003 | -0.003 |
| | (0.005) | (0.006) |
| Years of Education Squared | -0.001 | -0.001 |
| | 0 | 0 |
| Fraction of Discouraged People in the Household | | 0.085** |
| | | (0.018) |
| Constant | 1.370** | 1.320** |
| | (0.119) | (0.110) |
| Observations | 4847 | 4847 |
| R-squared | 0.08 | 0.16 |

*Notes:*

Data Source: Cape Area Panel Study Wave 4

* Significant at 5% Level; ** Significant at 1% Level

Robust standard errors in parentheses

The Network Effect Considers the Mean Incidence of Employment

Fixed effects for Age and Neighbourhood are Included

Whilst the estimated results in table 7 show similar results to table 6 with regard to the $\alpha$ coefficient, the estimated coefficient for the fraction of discouraged members of the household is positive and significant. This positive result indicates that, while individuals do not consider their broader social networks when deciding on their job availability, they do rely on their discouraged stronger ties. Individuals are swayed by the incidence of in-house discouragement.

## Understanding Discouragement

Following the lack of evidence of a network effect of labour discouragement, additional regressions were performed to further asses the causes of labour discouragement with regard to weaker social networks. These additional regressions assess whether the wide distribution of contacts available to individuals would result in insignificant results. In addition the model is re-run to assess whether there is a network effect for discouragement when the mean incidence of discouragement in the extended weaker network is considered.

In the data, the distribution of contacts available to individuals is very wide. Some individuals only had a few members of their age cohort in their neighbourhood while others had ample contacts. To test whether the isolated few individuals were causing the insignificant network effect result the data was ordered by contact availability and the most isolated 10% of the contacts were removed and the estimated regression was performed. In addition, the next most isolated 10% were also removed and the same set of regressions was performed once again. The results of these estimations are presented in table 8 below. The given results are consistent with the results presented in table 4. The network effect remains insignificant despite the dropping the relatively isolated contacts.

**Table 8: Regression Estimates of Network Coefficients: Inactive Contacts Removed**

| | Probability Unemployed Individual is Discouraged (Most isolated 10% of contacts removed) 1317 Obs deleted | | | Probability Unemployed Individual is Discouraged (Additional 10% of most isolated individuals removed) 1192 Obs deleted | | |
|---|---|---|---|---|---|---|
| | -1 | -2 | -3 | -1 | -2 | -3 |
| Contact Availability | 0.019 | 0.065 | 0.1 | 0.046 | 0.143 | 0.22 |
| | (0.046) | (0.047) | (0.072) | (0.058) | (0.064) | (0.109) |
| Network Effect | 0.193 | -0.221 | -0.416 | 0.119 | -0.624 | -0.014 |
| | (0.208) | (0.221) | (0.335) | (0.242) | (0.301) | (0.505) |
| Constant | 0.837** | 0.849** | 0.849** | 0.832** | 0.862** | 0.862** |
| | (0.009) | (0.02) | (0.021) | (0.011) | (0.022) | (0.025) |
| Observations | 4390 | 4390 | 4390 | 3942 | 3942 | 3942 |
| R-squared | 0.002 | 0.032 | 0.14 | 0.003 | 0.035 | 0.16 |
| Age Fixed Effects | NO | YES | YES | NO | YES | YES |
| Neighbourhood Fixed Effects | NO | NO | YES | NO | NO | YES |

*Notes:*
Data Source: Cape Area Panel Study Wave 4
* significant at 5% level; ** significant at 1% level
Robust standard errors in parentheses



As an increase in the incidence of discouragement in the network group could infer views of job prospects, prescriptions and peer pressures which may deter the entry to the job market, the estimation model is adapted to test whether the incidence of discouragement affects discouragement levels. The model looks as follows: $DISC_{ijk} = \left(C_{JK} \times \overline{DISC_k}\right)\alpha + X_i b + g_j + d_k + C_{jk} f + e_{ijk}$. Here the binary discouraged dependent variable is related to the network measure determined by the incidence of discouragement. If such pressures infer an effect on discouragement one would expect a significant $\alpha$ coefficient. The estimated results of discouragement given employment incidence in the network are given in table 9 below.

**Table 9: Discouragement on Discouragement Levels**

| | Probability that an Individual is Discouraged given Discouraged incidence | | |
|---|---|---|---|
| | -1 | -2 | -3 |
| Contact Availability | 0.046** | 0.026 | 0.018 |
| | (0.013) | (0.012) | (0.016) |
| Network Effect | 0.67** | 0.01 | -0.891 |
| | (0.176) | (0.176) | (0.233) |
| Constant | 0.844** | 0.835** | 0.84** |
| | (0.008) | (0.018) | (0.017) |
| Observations | 4847 | 4847 | 4847 |
| R-squared | 0.005 | 0.03 | 0.14 |
| Age Fixed Effects | NO | YES | YES |
| Neighbourhood Fixed Effects | NO | NO | YES |

*Notes:*

Data Source: Cape Area Panel Study Wave 4

* Significant at 5% Level; ** Significant at 1% Level

Robust Standard Errors in Parentheses



The results of table 9, like those given in table 4 suggest a lack of a network effect as the $\alpha$ coefficient is not significant when the fixed effects for age and neighbourhood are included. Prior to the inclusion of the fixed effects, however, there is a loosely significant network effect. This loss of significance, once again, highlights the importance of correcting for omitted variable bias as one would falsely conclude the presence of a network effect. The lack of network effect further confers the result that individuals do not rely on their broader social network when they make decisions on labour market involvement. Discouragement, therefore, reflects unobserved heterogeneity within age cohorts and neighbourhoods. The probability of discouragement appears to be largely based on personal psychological forces and is not affected by ones broader social network.

## Discussion and Conclusion

Given the general lack of empirical discussion on social networks in the labour market, this paper examines whether a network effect is present in labour market outcomes in the greater Cape Town region. The results indicate that while information transfers and social pressures from an individual's weak and strong contacts play an important role in employment, no weak tie network effect is evident for discouragement probability. For employment, the indirect effects of social network increase employment orientated policies by between 1.7 and 13%.

The method used in this paper is in line with those used by Bertrand *et al* (2000) and Burns *et al* (2010) and used proxy measures and a number of fixed effects to estimate network effects with minimal distortion from omitted variable bias. The lack of accounting for omitted variables would result in the over estimation of the network effects for employment and unemployment. Failing to account for omitted variable bias would have also resulted in an incorrect conclusion that labour discouragement is affected by the incidence of discouragement in an individual's weak social network.

The appropriateness of using age cohorts as opposed to language (Bertrand *et al,* 2000), race or age-language (Burns *et al* 2010) is conceptually justifiable in the South African context. Since South Africa is particularly fractured by race due to previously racially-oppressive legislation in terms of income and living area, networking by age-race or age-language is likely to have similar results. The premise that individuals of similar age who live in a common area would make a common social network does not appear to be farfetched. There is, however, some indication, given in the summary statistics, that there may be some variation on the network effect by race. There are, for example, variations in unemployment and discouragement rates between white and black individuals. In table 3, 97% of white unemployed individuals are discouraged compared with 81% of black unemployed individuals. In a South African context this could be the result of affirmative action policies which may have a despondency creating effect among the white unemployed. An alternative network proxy could involve using gender along with age, or language, or race may also lead to varied results[2]. There appears to be some variation in the discouragement values between males and females and it could be the case that there are stronger network effects for a gender.

The inconsistency among races and genders and the variation of network effects between weak and strong ties with regard to discouragement highlights the vast lack of understanding as to what influences the decision to become discouraged. It is vital that, for a better understanding on this effect, more psychologically apt research should be carried out in the future. Research should be done on the network effect evident only among discouraged strong ties, to better assess this transmission mechanism.

[2] The use of network contacts in the job search, according to Ioannides and Loury (2004: 1057), varies depending on race, gender and education of individuals.

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