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Longitudinal Surveys of
Australian Youth

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NEIGHBOURHOOD EFFECTS AND COMMUNITY SPILLOVERS IN THE AUSTRALIAN YOUTH LABOUR MARKET

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EXECUTIVE SUMMARY

Neighbourhood effects refer to the situation whereby residential location impacts on the social outcomes of individuals, above and beyond what would be expected from their personal and family characteristics. That is, it is the “residual effect” on social and economic outcomes once the impacts of personal ability and family background have been controlled for.

A number of theories of neighbourhood effects exist. These can be broadly classified as: theories of collective socialisation theories; contagion-based or “epidemic” theories; and information network theories.

Existing Australian research has focused mainly on the impact of neighbourhoods on youth education decisions. In contrast, this study models the probability of unemployment as a function of personal characteristics, family structure and neighbourhood composition. Cross-sectional and panel data approaches are used to model this relationship.

- In the study here, the relationship between youth unemployment and neighbourhood composition was first examined in two cross-sections: an 18 year-old and a 21 year- old group. Binomial probit estimation techniques were used to establish the influences of personal characteristics, family background and neighbourhood composition on the probability of an individual being unemployed.

Findings

- The cross-sectional model indicates that significant neighbourhood effects on unemployment outcomes exist in high and low-income areas. While the positive effects of living in a high-income neighbourhood diminish by the age of 21, the negative effects associated with low-income neighbourhoods persist.

- The neighbourhood concentration of vocational qualifications is also a significant factor in the cross-sectional model. Specifically, it is found that low concentrations of such qualifications affect the unemployment outcomes of young people. This could be an indicator of the weaker employment and information networks that typically exist in low-income neighbourhoods.

- The panel data model indicates that unobserved heterogeneity is an important factor in the modelling of neighbourhood effects. In this case, unobserved heterogeneity refers to unobservable individual characteristics (for instance motivation) that influence the probability of being unemployed.

- This panel model confirms the presence of neighbourhood effects in the lowest 20% of neighbourhoods by income but does not corroborate the existence of effects related to the concentration of vocational qualifications.

Neighbourhood Effects and Community Spillovers in the Australian Youth Labour Market

1

INTRODUCTION

On average, young people from affluent areas have higher levels of education, are less likely to be unemployed, and perform better in the labour market than their counterparts from poor areas (Jencks & Mayer 1990: 111). This would seem to imply that the quality and composition of a youth's residential 'neighbourhood' has a direct impact on their social and economic outcomes. However, this apparent causal link may be spurious. For example, children from affluent families may outperform those from poor families irrespective of the neighbourhood they grew up in. If this is true, it could be that the spatial dimension of disadvantage reflects families with similar characteristics sorting together geographically. This may mean that socio-economic disadvantage is not generated from *within* neighbourhoods. Instead, urban disparity merely reflects broader inequalities in the economy (Borland 1995).

For practical purposes this is an important distinction. If 'neighbourhoods matter', it is socially undesirable to allow undue concentrations of disadvantage to persist at a local level. If, however, apparent neighbourhood effects merely reflect wider trends of inequity, neighbourhoods in themselves do not present a specific issue for public policy. Practically, the presence of neighbourhood effects suggests a need to add an extra dimension to the agenda of welfare reform. That is, insofar as welfare reform has focused mainly on the relationship between individuals and the welfare system, the presence of neighbourhood effects suggests that other policy mechanisms are necessary to combat community-level externalities and spillovers.

This report investigates the role of neighbourhoods on youth labour market outcomes and distinguishes its effects from the influence of the "traditional" determinants of social disadvantage, such as family and personal characteristics. The report proceeds as follows. Section 2 provides a review of existing research, definitional issues and theories of neighbourhood effects. Section 3 provides an overview of data that describes the links between neighbourhood inequality, educational outcomes and youth labour market performance in Australia. Section 4 introduces a cross-sectional approach to modelling unemployment in the presence of neighbourhood inequality. Section 5 outlines a panel data model of neighbourhood that analyses the links between neighbourhoods and individuals latent probability of being unemployed. Finally, Section 6 consolidates the findings from the study, and discusses the policy implications of our research.

2

NEIGHBOURHOOD EFFECTS AND LABOUR MARKET OUTCOMES

Neighbourhood Effects - Definition

Neighbourhood effects refer to the situation whereby residential location impacts on the social outcomes of individuals, above and beyond what would be expected from their personal and family characteristics. That is, it is the "residual effect" on social and economic outcomes once the impacts of personal ability and family background have been controlled for. Hence, neighbourhood effects represent externalities at a local community level, whereby individuals' decisions spillover and affect the decision making and outcomes of other members of a local area.

The term neighbourhood itself has a broad meaning. It has been used to categorise regional areas ranging from immediate (next door) neighbours through to postcodes or census areas. Due to data constraints, quantitative studies have traditionally emphasised larger neighbourhood areas, in particular postcodes/zip codes or school attendance areas[1]. Despite these differences in interpretation, a common theme is that neighbourhoods are distinctly geographic in nature, and do not refer to other forms of social networks such as ethnic groups.

Theories of Neighbourhood Effects

A number of theories have been proposed that link neighbourhood composition to youth outcomes and decision-making. These can be broadly categorised into three types: theories of collective socialization, contagion-based or "epidemic" theories and network / information theories. All three are theories of localized spillovers that lead to sub-optimal social and economic outcomes. They do, however, differ markedly in the terms of the mechanism through which neighbourhood disadvantage is generated and reinforced.

Collective socialization refers to the idea that an individual is conditioned by the type of role models they are exposed to during childhood. This approach emphasises the effect of adult role models apart from an individual's parents. Due to the limited geographical mobility of children, they will most frequently come into contact, and attend institutions such as schools and churches, with adults and children who live in the same neighbourhood. As a result, children from the least affluent neighbourhoods will have different role models and peers to those from the most affluent neighbourhoods. This difference will range from exposure to criminal activity and other forms of negative social outcomes (for instance, teenage pregnancy and illicit drug use) through to levels of adult educational attainment and labour market activity in their local area. In turn, this leads to the development of differential norms.

Furthermore, the act of sorting means that those families living in poorer areas who do manage to "succeed" will be likely to move to a better neighbourhood[2]. This process makes it difficult to "sustain basic institutions … including churches, stores, schools,

1 A notable exception is Case & Katz (1991) who used the NBER Boston Youth Survey. From this survey it was possible to identify the individual's residence at a housing block level.

2 Sorting refers to the tendency for people to socially and geographically separate along lines of income or wealth (Tiebout 1956).

recreational facilities" that normally serve to promote positive social behaviour (Wilson 1987; Rosenbaum and Popkin 1991).

The re-inforcement of norms at a neighbourhood level leads to herd behaviour, which operates through the channel of epidemic or contagion effects. (Case & Katz 1991). Children learn societal norms from the adult role models they come in contact with most often, which in turn is re-inforced by their interaction with each other. It has been suggested that this type of feedback leads to the contagion of disadvantage at a neighbourhood level (Crane 1991). The lower the quality of the neighbourhood, the more likely it is that successful families/individuals will seek to move elsewhere. If unchecked this may lead to the cumulative geographical pooling of socio-economic disadvantage.

Alternatively, the type of residential area that a child grows up in may affect their knowledge of the returns to crucial decisions (such as whether to complete high school), and their access to social networks. Specifically, spatial inequality can give rise to information asymmetries. For example, Jencks and Mayer (1991) argued that young people who are from neighbourhoods where high school completion and tertiary education are less common will on average underestimate the returns to education. Hence, youth from these neighbourhoods will choose a sub-optimal level of education. Conversely, individuals from neighbourhoods where high school completion and tertiary qualifications are the norm may overestimate the returns to education.

Information asymmetries may also affect an individual's ability to gain employment. Individuals from neighbourhoods where fewer people hold permanent positions may have less knowledge of job opportunities. Informal job networks such as personal contacts have been found to be the leading method individuals use to search for and gain employment (Holzer 1987, 1988; Montgomery 1991). At the same time, neighbourhood composition may lead to demand side neighbourhood effects (Borland 1995; Montgomery 1991). For instance, if an employer is faced with two applicants who have identical personal characteristics, but one is from a less favourable neighbourhood, the employer may use this information as a signal of what are called unobservable characteristics. These characteristics include traits such as motivation and innate ability that cannot be detected through formal employment selection mechanisms. In this situation applicants from poorer quality neighbourhoods may be discriminated against in the job application process. More explicitly, the reliance of hiring decisions on inside information (such as personal references from members of the work force) may discriminate against individuals who do not have active contacts within the permanent workforce.

It is possible though that youth labour market outcomes may be contingent on location where no neighbourhood effect is apparent. If employment opportunities are distributed unevenly across urban locations, differences in the labour market performance of youth may reflect spatial mismatch in the labour market (Kain 1968). The spatial mismatch hypothesis proposes that it is unequal spatial demand for labour that gives rise to urban inequalities in labour market performance. However, evidence on the spatial mismatch hypothesis has been ambiguous (Mayer 1996).

Empirically identifying the effect of neighbourhoods is likely to be problematic for a number of reasons. It has been established that family characteristics have a substantial impact on youth labour market performance in Australia (Miller 1998). Due to sorting, the impact on youth outcomes of neighbourhoods and family characteristics are likely to be highly correlated. Hence, any empirical approach to modeling neighbourhood effects must control for the sorting of family characteristics. Also, the identification and measurement of endogenous peer effects is potentially problematic. Manski (1993) demonstrates that inferences regarding social behaviour based solely on the observed behaviour of individuals from sample data are at best tenuous.

Despite the level of theoretical detail concerning how neighbourhoods might affect youth outcomes, it is difficult to empirically validate any one of these theories (Borland 1995). A key problem is the observational equivalence of many of these theories. That is, despite the differences in the mechanisms they describe, the predicted social and economic outcomes are similar. The pooling of disadvantage creates localised spillovers, which in turn lead to sub-optimal outcomes for youth. Hence, while it may be possible to establish whether neighbourhood effects are important, theory testing and the identification of specific channels of effect is more problematic.

Existing Australian Evidence

Australia lacks the severe poverty, crime and social dislocation apparent in many parts of the United States. Despite this, the past decade has witnessed a growing concern in Australia with issues related to urban inequality. Recently, this has resulted in a number of papers assessing the impact of neighbourhoods on youth outcomes and decision making. With the exception of Andrews (2000), these studies have focused on the link between neighbourhood composition and youth decisions on education.

Two studies have used cross-sections drawn from the Australian Youth Survey (AYS) to assess the relationship between neighbourhood composition and youth education decisions (Heath 1999, Overman 2000). The main method used in both studies is to estimate a probit model of Year 12 non-completion where a number of personal and family characteristics have been controlled for. Both studies indicate that Year 12 completion rates are inversely related to the proportion of adults (but not the individual's parents) in the neighbourhood with vocational qualifications. However, they differ in regards to the explanation given for this finding. The Overman (2000) study attributed this result to local labour market conditions in terms of the increased availability of jobs that did not require high school completion. A distinction was made in that study between small neighbourhoods based on census collection districts and large neighbourhoods based on postcodes. The vocational training effect was only apparent at the large neighbourhood level. Overman (2000) suggested that this reflected labour market conditions at a large neighbourhood level, but did not represent the channel for endogenous social effects at the small neighbourhood level. For small neighbourhoods, the socioeconomic level of the area has the main influence on school drop-out rates. Heath (1999) also found evidence of vocational qualifications level impacting on non-completion rates, but explained this in terms of neighbourhoods effect on youths' perception of the returns to high school completion.

Jensen and Seltzer (2000) used a survey of 171 Year 12 students from ten government schools in Melbourne. They estimated the role of neighbourhood effects on the decision to attend post-secondary education in a framework that also controlled for personal and family characteristics. They found evidence of neighbourhood effects, in particular, a strong negative correlation between neighbourhood unemployment levels and post-secondary education decisions. They note that:

> ..with over six percent of Local Government Areas (LGAs) in Australia having unemployment rates over 15 percent, these results raise concerns that a large number of neighbourhoods are generating negative externalities that could severely retard educational progress (Jensen & Seltzer 2000: 26).

Additionally, they found that peer effects mattered - students who believe that the majority of their peers will undertake post-secondary education are 14 per cent more likely to undertake future education themselves.

So far there has been little Australian research linking neighbourhood composition to labour market outcomes. Andrews (2000) represents the only econometric modeling of this relationship to date. Two approaches were implemented. Firstly, a binomial model of unemployment probability was estimated for a sample of 18 year olds. Secondly, a multinomial logit technique was used to model the impact of neighbourhoods on the likelihood of an individual being unemployed or not in the labour force[3]. Using data from the AYS, Andrews (2000) found evidence that being from a neighbourhood where a low proportion of adults held vocational qualifications, or where neighbourhood income levels were low, significantly increased the probability of youth unemployment. Results from the multinomial logit indicated that vocational qualifications of neighbourhood adults decreased the probability of youth being unemployed. High relative levels of neighbourhood personal income and adult holdings of degree qualifications increased the likelihood of an individual not being in the labour force.

3 For this age group, not in the labour force consisted predominantly of individuals undertaking full-time study.

3

THE URBAN CONCENTRATION OF DISADVANTAGE IN AUSTRALIA

This chapter provides a brief overview of the nature of urban inequality in Australian cities. In particular, it focuses on data relating to the correlation between neighbourhood quality and youth labour market and education outcomes. This data is sourced primarily from the Australian Youth Survey (AYS).

Evidence of Urban Inequality in Australia

The past decade has witnessed a growing emphasis on urban inequality in Australian economics. In particular, a number of papers have drawn attention to the growing income inequality in urban Australia that has occurred over the past 25 years. As early as 1971, substantial unemployment differentials were found to exist across Sydney (Vipond 1980). Similar evidence was found for Melbourne in 1976 and 1981 (Beed et al 1983). However, it was not until the mid-1990s that a substantial literature on Australian urban inequality began to form. Gregory and Hunter (1995) found that the growing level of urban inequality is primarily the result of an increasing spatial disparity in unemployment rates. Similarly, Hunter (1995) showed that employment levels per capita in urban census collection districts have polarised between the 1975-1991 census periods. Clearly then, the evidence is that increases in urban inequality are, at least in part, a result of increasing spatial differentials in the labour market success of individuals.

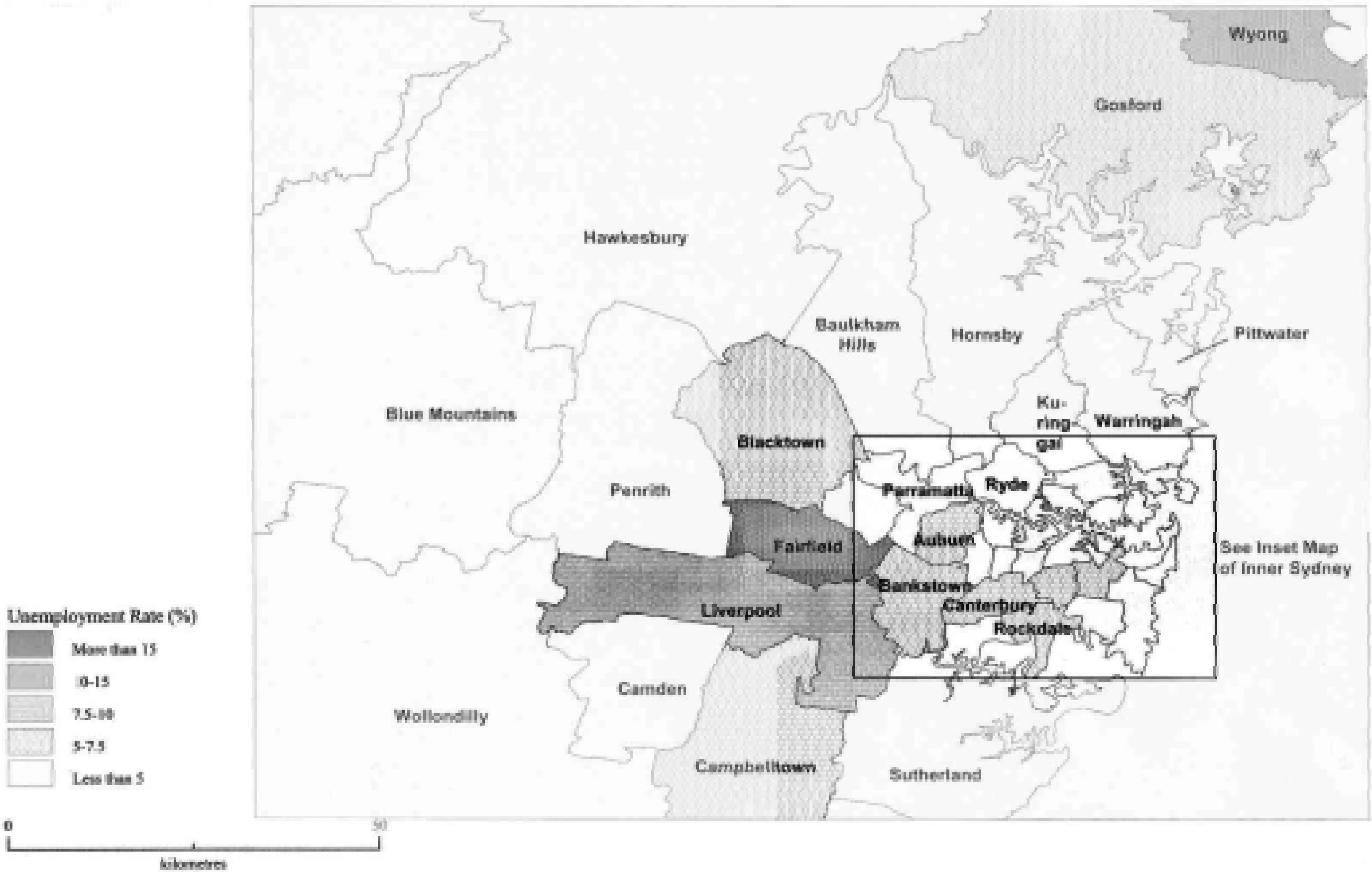
Figures 3.1 and 3.2 display the distribution of unemployment rates across Australia's two largest cities. Both have pools of unemployment, areas that exhibit average unemployment rates of roughly 2-3 times the rate of low unemployment areas. Areas with high unemployment rates are generally adjacent to mid-to-high unemployment level areas. The most disadvantaged areas are geographically isolated from low unemployment areas.

Education and Labour Market Outcomes in the AYS

Table 3.1 displays a range of **personal characteristics** as at age 21 (unless stated otherwise) taken from the Australian Youth Survey (AYS). This is split according to the income level of the neighbourhood the respondent was living in at time of first interview (generally 16 but sometimes older)[4]. Data is reported for those individuals living in the top two deciles, the middle, and the bottom two deciles of the neighbourhood income distribution.

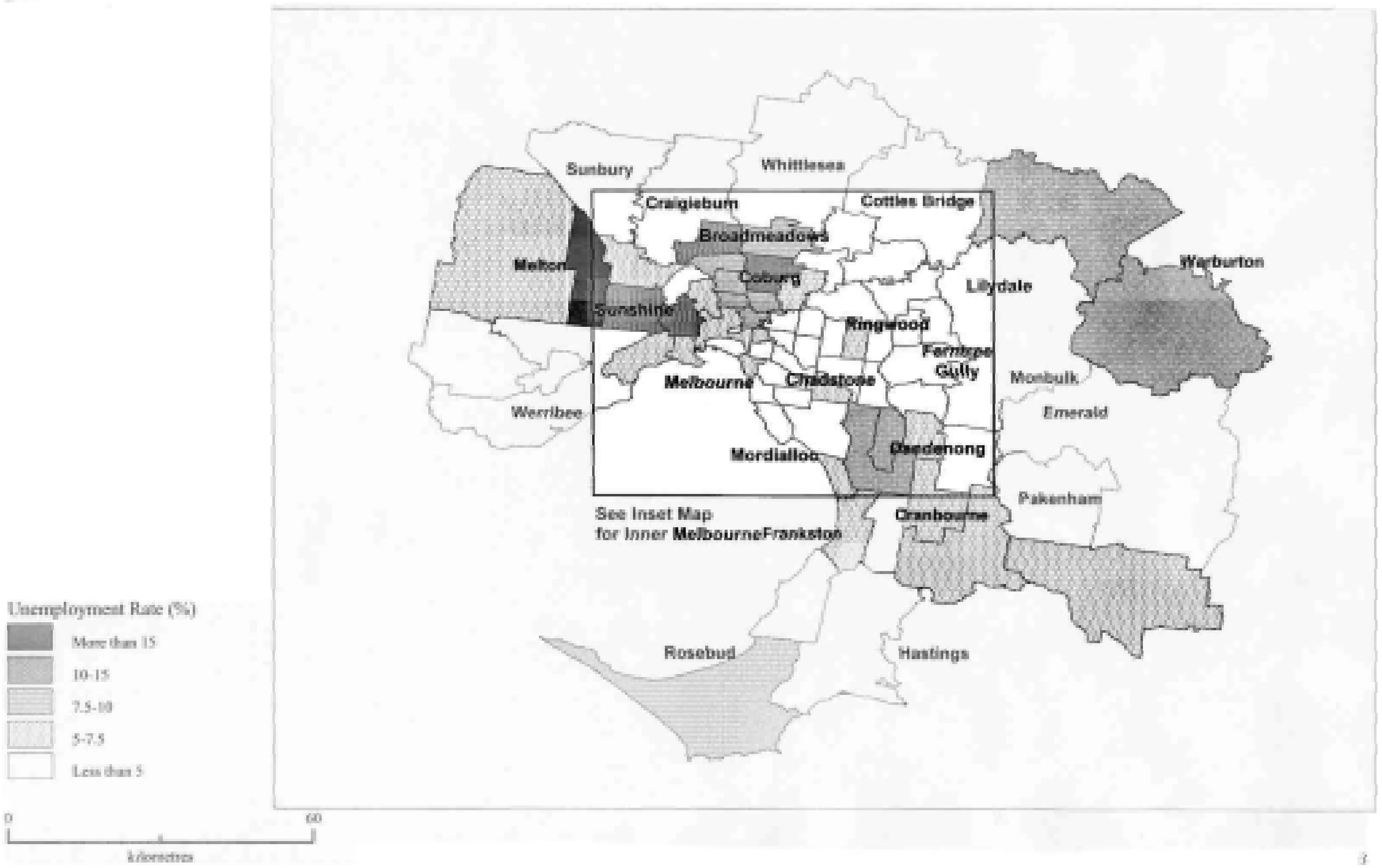
4 All neighbourhood variables are for the adult population (18 years +) taken from the 1991 census. The earliest respondents in the AYS are from 1989 and predominantly were either 16 or 17 years old at this time. Hence potential within sample bias, for instance between neighbourhood income and AYS respondents unemployment rate, should be minimal.

Figure 3.1 Unemployment Rates by SLA in the Sydney Statistical Region, 2000



Source: DEWRSB Small Area Estimates

Figure 3.2 Unemployment Rates by SLA in the Melbourne Statistical Region, 2000



Source: DEWRSB Small Area Estimates

Table 3.1 Personal Characteristics by Neighbourhood Income

	Whole Sample	NHINC <20*	NHINC Mid	NHINC >80**
Sample Size	3,345	667	1,996	682
Male	52.6%	53.2%	53.1%	51.4%
NESB	9.4%	9.9%	9.5%	8.9%
ATSI	1.1%	1.3%	1.1%	0.5%
Unemployment	14.5%	19.8%	14.2%	11.1%
Full-Time Study	7.7%	7.8%	7.0%	10.0%
Year 12 Completion	84.8%	82.8%	83.8%	90.1%
Degree Completion	10.3%	7.7%	10.0%	13.9%
Trade Qualification	7.8%	9.3%	8.1%	5.6%
Government School	69.2%	84.3%	71.0%	50.9%

Source: AYS, DEET (1996)

*NHINC < 20 = Individuals who reside in neighbourhoods that are in the lowest 20% of the neighbourhood income distribution
**NHINC > 80 = Individuals who reside in a neighbourhoods that are in the highest 20% of the neighbourhood income distribution

Unemployment rates decrease as neighbourhood income increases. It must be recognised, however, that those in the most affluent neighbourhood also have a higher full-time study rate. This will bias the unemployment figures downwards for affluent neighbourhoods. Year 12 completion rates are only substantially higher for those in the top two deciles. However degree completion rates increase steadily with neighbourhood income. Youth from poorer neighbourhoods appear more likely to pursue trade qualifications, which may reflect the negative correlation between proportion of adults with vocational qualifications and neighbourhood income (see Table 3.3). Finally, government school attendance is markedly lower for youth from the highest two decile neighbourhoods; 50.9 per cent attending government run schools compared with 84.3 per cent of youth from the lowest two deciles.

Table 3.2 Family Characteristics by Neighbourhood Income

Parents/Family	Whole Sample	NHINC <20	NHINC Mid	NHINC >80
Single Parent	14.3%	16.4%	14.0%	13.5%
No Parent	1.4%	1.2%	0.9%	1.2%
One Parent Not Working	40.2%	44.0%	39.8%	37.7%
Both Parents Not Working	2.7%	4.0%	2.8%	1.0%
Parent Tertiary	19.7%	12.0%	18.7%	40.6%
Both Parents Tertiary	6.0%	1.9%	4.6%	14.1%
Parent Trade Qualification	16.2%	19.1%	21.8%	14.1%
Both Parents Trade	2.9%	2.5%	2.0%	2.1%
Living at Home @ 18 yrs	87.7%	88.0%	87.8%	87.0%

Source: AYS, DEET (1996)

Table 3.2 displays the distribution of family characteristics by neighbourhood income, and provides some evidence on sorting. Unlike the US data, there are not significant differences in single parent or no parent present rates according to neighbourhood income. There is, however, an indication that greater proportions of youth from poorer neighbourhoods have either one or both of their parents not attached to the work force. Youth from the highest two deciles are 22 per cent and 28 per cent more likely to have a parent with tertiary qualifications than those from the mid category and the lowest two deciles respectively. They are also substantially more likely to have two parents with tertiary qualifications.

Table 3.3. displays "neighbourhood quality" correlations between a number of personal and family characteristics and three measures of neighbourhood composition. These measures are the level of neighbourhood income (NHINC), the proportion of adults with degree qualifications (NHDEG), and the proportion of adults with skilled vocational qualifications (NHVOC). The correlations show that neighbourhoods with high income levels are also likely to have relatively large proportions of individuals with degree qualifications. There is a weak negative relationship between neighbourhood vocational qualifications and neighbourhood income. Neighbourhoods with a high proportion of degree holders are not likely to have a high proportion of individuals with vocational qualifications.

As may be seen from the data in Table 3.3, neighbourhood income is positively correlated with full-time study and Year 12 and degree completion; it is negatively correlated with unemployment and public school attendance. Neighbourhood degree holdings are inversely related to unemployment and public school attendance. Stronger positive correlation exists between adult degree holding and Year 12 and degree completion. Conversely, neighbourhood vocational qualifications are negatively correlated with Year 12 and degree completion and full-time study rates.

Table 3.3 Correlation Matrix for Neighbourhood Quality

	NHINC	NHDEG	NHVOC
Yr12 Comp @ 21 years	0.118	0.157	-0.101
Degree @ 21 years	0.093	0.119	-0.058
Trade @ 21 years	-0.056	-0.102	0.106
Full-Time Study @ 21 years	0.050	0.050	-0.072
Unemployment @ 21 years	-0.076	-0.043	-0.045
Government School	-0.234	-0.237	0.111
ATSI	-0.027	-0.041	0.028
NESB	-0.015	-0.031	-0.091
Parent Not Employed	-0.034	-0.037	0.015
Parent Tertiary Educated	0.254	0.270	-0.080
NHINC			-0.084
NHDEG	0.821		
NHVOC		-0.427	

Source: AYS, DEET (1996)

4

CROSS SECTIONAL MODEL – NEIGHBOURHOOD EFFECTS AND UNEMPLOYMENT

This section outlines a cross-sectional approach to modelling the impact of neighbourhoods on unemployment. The aim is determine whether, once personal and family characteristics are controlled for, neighbourhood composition provides a significant indicator of unemployment propensity.

After controlling for these family characteristics we test for the presence of neighbourhood effects related to three neighbourhood variables based on income and the concentration of vocational and degree-level qualifications. Three main findings are evident from our modelling:

- At the 18-year old level, we find that there are significant neighbourhood effects apparent for low and high-income. This is consistent with the process of labour market polarisation described by various theories of neighbourhood effects. Furthermore, the positive effects of living in a high-income neighbourhood diminish by the age of 21 while the negative effects associated with low-income neighbourhoods persist.

- The concentration of skilled vocational qualifications influences the probability of unemployment. Low concentrations of such qualifications are a disadvantage to young job-seekers and are suggestive of the weaker employment networks that prevail in such areas. The strength of this effect diminishes by the age of 21 but still remains statistically significant.

- The concentration of degree-level qualifications does not appear to influence the probability of unemployment. It is possible that this variable is a determinant of full-time post-secondary study patterns instead. This would explain why it does not interact directly with the probability of being unemployed at age 18 or 21.

Data

Two samples were constructed from the AYS; a sample of 2,745 18 year olds and a sample of 3,089 21 year olds. Both samples were drawn from across a number of AYS cohorts. A complicating factor is that during the conduct of the AYS the sampling method was changed from random population sampling to school based sampling. To check for bias caused by this difference in sampling methods a number of tests for structural breaks between the cohorts were conducted. No evidence of structural change was found in either sample. As a precaution, however, a control (Year) is maintained in all the specified models.

To restrict the focus to those individuals either currently working or currently looking for work, both samples omit individuals undertaking full-time study. Using these two samples, the effect of neighbourhoods on labour market outcomes can be assessed at two distinctly different points of early labour market experience.

The AYS is chosen as the data source for two main reasons: it reports a detailed range of family background characteristics, and more importantly the respondent's post code was recorded and included in the data file. Details of all the variables used in the cross-sectional models, and the panel models in Section 5, are included as Appendix 1. The personal characteristics included in the sample are all standard and do not require further discussion here.

A number of controls are included for the family characteristics of the individual. These broadly cover three areas; family composition, parents' education and parents' employment status (all reported at age 14). Family composition is defined in terms of two parent, single parent, or no-parent present family. The highest level of educational attendance of at least one of the respondent's parents is controlled for. Finally, dummies for whether the individual had a parent not attached to the work force is included.

Neighbourhood variables are defined in terms of residential postcode as at first interview (generally at age 16). This explicitly controls for the endogeneity between neighbourhood characteristics and labour market outcomes that might occur due to migration. Importantly, this means that we are examining the impact of the quality of the neighbourhood the youth has grown up in, rather than the local labour market conditions of the area they reside in at age 18 and 21. State variables (included as dummies with NSW the default case) refer to the location of the individual at age 18 and 21 respectively, and thus capture differences in state labour market conditions.

Three measures of neighbourhood quality are used; the level of income in the neighbourhood (NHINC), the proportion of neighbourhood adults who possess degree qualifications (NHDEG), and the proportion of neighbourhood adults who possess vocational qualifications (NHVOC). These measures are all taken from the adult population (18 years on) of the 1991 Census. As this is near the beginning of the AYS sample period it reduces the possibility for sorting based endogeneity problems in the neighbourhood quality measures. The use of an outside data source (i.e. not the AYS) to characterise neighbourhood quality, and the focus on the adult population's effects on youth, also allow us to avoid the 'reflection' problem outlined by Manski (1993). We discuss each measure in turn:

- Neighbourhood income (NHINC) is used as a proxy for the economic situation of a particular neighbourhood. This captures the impact of concentrations of affluence, and economic disadvantage on youth employment outcomes.

- Neighbourhood degree (NHDEG) is used as a proxy for information on returns to education and exposure to tertiary educated role models. Hence it is highly correlated with youth high school and degree completion rates. It is unclear a priori what effect, if any, this will have on the probability of a youth being unemployed.

- Neighbourhood vocational training (NHVOC) is used as a proxy for access to informal job networks for jobs where Year 12 and / or degree completion may not be required. In previous studies NHVOC has been linked with high school non-completion and lower youth unemployment (Heath 1999, Overman 2000).

While these variables proxy different aspects of neighbourhood composition, it must be recognized that they are likely to be highly correlated. This is a major problem given the relatively small sample sizes and small numbers of individuals per neighbourhood we have here[5]. This may lead to difficulty in attaining statistically significant coefficients on any of the neighbourhood variables if they are all included within the same multivariate analysis. As an alternative approach we also estimate separate models for each of the neighbourhood variables[6].

Finally, a major concern of the neighbourhood effects literature is the impact of concentrations of neighbourhood disadvantage on social and economic outcomes (Case & Katz 1991, Crane 1991). Continuous neighbourhood variables cannot adequately capture these effects. Hence, dummy variables are used to categorise youth as being in either the bottom or top two decile units of the distribution for each neighbourhood variable.

Econometric Methodology

The unemployment probability for individual *i* is given by:

$$Y_i^* = \alpha + \beta_1 X_i + \beta_2 F_i + \beta_3 N_{ij} + \varepsilon, i = 1,...,n; j = 1,...,m \tag{4.1}$$

Where: X_i is a vector of characteristics for individual *i*;
F_i are the family characteristics for individual *i*; and
N_{ij} are the characteristics of neighbourhood j for individual *i*.

The underlying response variable y* in equation (1) is defined by the relationship;

$$y_i^* = \beta' x_i + u_i \tag{4.2}$$

However, the probability of an individual being unemployed (y_i*) is unobservable, instead we observe a dummy variable y_i, defined as

$y_i = 1$ if $y_i^* > 0$

$y_i = 0$ otherwise.

As a result, equation 4.1 is estimated through the use of a probit regression.

5 Typically there are between 2 to 6 individuals per post code, although there are a small number of post codes with 8 or 9 individuals.

6 This is in line with much of the US literature on neighbourhood effects where generally only one measure of neighbourhood composition is included as an independent variable. This was also the approach of Jensen and Seltzer (2000).

Table 4.1 Estimates from Cross-Sectional Models

	Average Effects		Marginal Effects	
	18 Years	21 Years	18 Years	21 Years
Constant	4.4 (2.26)	0.60 (2.5)		
Year	-0.06 (0.02)**	-0.02 (0.03)	-0.02** (0.01)	-0.01 (0.01)
Male	-0.06 (0.06)	0.21* (0.06)	-0.02 (0.02)	0.05* (0.01)
Vic	0.13 (0.08)	0.22* (0.08)	0.04 (0.02)	0.05* (0.02)
Qld	-0.06 (0.08)	-0.15 (0.10)	-0.02 (0.02)	-0.03 (0.03)
SA	0.08 (0.10)	0.05 (0.11)	0.03 (0.03)	0.01 (0.03)
WA	-0.11 (0.10)	0.06 (0.11)	-0.03 (0.03)	0.01 (0.03)
Tas	0.24 (0.16)	0.35** (0.16)	0.07 (0.05)	0.08** (0.04)
NT	0.44 (0.30)	0.12 (0.37)	0.13 (0.09)	0.03 (0.08)
ACT	0.11 (0.19)	-0.16 (0.26)	0.03 (0.06)	-0.04 (0.06)
ATSI	0.42**(0.21)	0.09 (0.26)	0.13** (0.07)	0.02 (0.06)
NESB	0.41* (0.11)	0.41* (0.10)	0.12* (0.03)	0.09* (0.02)
Less than Year 10	0.60* (0.17)	0.30 (0.20)	0.18* (0.05)	0.07 (0.05)
Year 10	-0.03 (0.08)	0.01 (0.05)	-0.01 (0.02)	0.02 (0.11)
Trade		-0.48 (0.10)*		-0.11* (0.03)
Degree		0.05 (0.99)		0.01 (0.02)
Government School	0.12 *** (0.07)	0.25* (0.07)	0.04*** (0.02)	0.06* (0.02)
Country Town	-0.01 (0.07)	0.03 (0.09)	-0.01 (0.02)	0.01 (0.02)
Rural	-0.30 *(0.11)	0.06 (0.17)	-0.09* (0.03)	0.01 (0.04)
Other City	0.05 (0.08)	0.16** (0.08)	0.02 (0.02)	0.04** (0.02)
Single Parent Family	0.26* (0.09)	0.28* (0.09)	0.08* (0.03)	0.06* (0.02)
Neither Parent Present	0.53*** (0.29)	0.46*** (0.25)	0.16*** (0.09)	0.11*** (0.06)
Pno education	0.32 (0.43)	0.37 (0.39)	0.09 (0.13)	0.09 (0.09)
Pprim	0.31*** (0.16)	0.16 (0.14)	0.09*** (0.05)	0.04 (0.03)
Ptrade	-0.16*** (0.09)	-0.10 (0.09)	-0.04*** (0.03)	-0.02 (0.02)
Pdeg	-0.01 (0.07)	0.07 (0.08)	-0.002 (0.02)	0.02 (0.02)
Parent Not Employed	0.10*** (0.06)	0.13** (0.06)	0.03*** (0.02)	0.03** (0.01)
NHINC20	0.12 (0.08)	0.11 (0.08)	0.04 (0.02)	0.03 (0.02)
NHINC80	-0.32* (0.10)	-0.15 (0.11)	-0.10* (0.03)	-0.04 (0.03)
NHDEG20	0.14 (0.11)	0.07 (0.08)	0.01 (0.02)	0.02 (0.03)
NHDEG80	-0.05 (0.07)	0.10 (0.11)	0.04 (0.03)	0.02 (0.02)
NHVOC20	0.21* (0.08)	0.04 (0.08)	0.06* (0.02)	0.01 (0.02)
NHVOC80	0.03 (0.08)	0.11 (0.08)	0.01 (0.02)	0.03 (0.02)
McFadden r^2	0.06	0.06		
Class Rate	76.2%	80.6%		
$P>\chi^2$	0.00	0.00		
Sample Size	2,745	3,089		

Numbers in parentheses are standard errors.

, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.*

Results

Table 4.1 reports the results from the estimated probit equations for unemployment. Generally, the impact of individual characteristics on the probability of being unemployed are as expected, with two main exceptions. At the ages of 18 and 21, the impact of education on the likelihood of unemployment has not manifested itself. Although, those who seriously underachieve (less than Year 10 completion) face an increased probability of unemployment, and those who have completed trade qualifications at age 21 face a marked reduction in the probability of unemployment. While it is significant and positive at age 18, ATSI has no significant effect on unemployment probability at age 21. This seems surprising. It is likely to be a result of the small cell sizes in the dataset (only just over 1 per cent of the 21 year old sample self-identified as ATSI).

As in other Australian studies (Bradbury *et al.* 1986, Miller 1998) family characteristics appear to have an impact on youth unemployment. Youth from a single parent family, or a family where neither parent is present, are significantly more likely to be unemployed. Likewise, having a parent who is not employed also increases the probability of a youth being unemployed. For 18 year olds, having a parent who holds a trade qualification is weakly significant and reduces unemployment probability; having a parent with less than high school education weakly increases the likelihood of being unemployed.

Estimating equations where all three measures of neighbourhood quality are included provides at best weak evidence of neighbourhood effects. For the 18 year old sample, growing up in an area with a relatively low proportion of vocationally skilled adults increases the probability of being unemployed; youth from areas with high income levels face a lower probability of being unemployed. The weakness of this evidence is potentially due to the high level of correlation between these variables, especially neighbourhood income and neighbourhood degree. To investigate this, separate equations are estimated where only a single neighbourhood characteristic variable is included in each. Table 4.2 reports the results from these equations for each of the neighbourhood variables[7].

Table 4.2 Separate Equation Estimates

	18 Years		21 years	
	Average Effects	Marginal Effects	Average Effects	Marginal Effects
NHINC20	0.13** (0.07)	0.04** (0.02)	0.14** (0.07)	0.03** (0.02)
NHINC80	-0.19** (0.08)	-0.06** (0.02)	-0.08 (0.08)	-0.02 (0.02)
NHVOC20	0.22* (0.07)	0.07* (0.02)	0.12*** (0.08)	0.02 (0.02)
NHVOC80	-0.04 (0.07)	-0.01 (0.02)	0.006 (0.08)	0.01 (0.02)
NHDEG20	0.04 (0.07)	0.01 (0.02)	0.03 (0.08)	0.03*** (0.02)
NHDEG80	0.01 (0.08)	0.003 (0.02)	0.12 (0.07)	-0.002 (0.02)

Standard errors are in parentheses

, ** and * represent statistical significance at the 1%, 5% and 10% level respectively*

7 Estimates for personal and family characteristics are not reported, as they do not change markedly from those displayed in Table 4.1.

For 18 year olds there appears to be an effect from living in either a high or low-income neighbourhood. Whilst the positive effect from growing up in a high-income neighbourhood diminishes by the age of 21, the adverse low-income effect persists. This result implies an ongoing adverse impact throughout early adulthood for individuals who have grown up in a less affluent neighbourhood. Youth from neighbourhoods with low proportions of vocational adults also appear to fare worse in the labour market. Youth who do not have access to the opportunities afforded by a strong local emphasis on skilled vocational qualifications may find it more difficult to gain employment. The skilled vocational effect diminishes substantially (both in size and significance) for 21 year olds. There is no evidence in any of the specifications that neighbourhood degree has a significant impact on the probability of being unemployed.

Conclusion

The results from the cross-sectional modelling indicate that neighbourhood composition, in particular income and the proportion of adults with vocational training, have an impact on the probability of youth unemployment above and beyond what is explained by personal and family characteristics. A difficulty is that estimates on neighbourhood variables drawn from cross-sectional analysis provide correlations, albeit tightly controlled correlations, between neighbourhood composition and labour market outcomes. Nonetheless, evidence drawn from the cross-sectional modelling provides the justification for the use of a more sophisticated panel framework that estimates the impact of neighbourhoods across early adulthood labour market experience. Furthermore, by making use of the longitudinal nature of the AYS, attempts can be made to control for individuals' unobserved heterogeneity. This is the aim of the next section.

5

A PANEL DATA MODEL OF UNEMPLOYMENT

In this section a panel data model aimed at a more robust assessment of the interaction of neighbourhood structure and unemployment outcomes over early adulthood is described and estimated. In particular, a model of unemployment is estimated that includes controls for the unobserved heterogeneity of individuals, and tracks their early labour market experience. In turn, this provides a more thorough examination of the potential for neighbourhoods to impact on youth labour market outcomes.

This panel data model has a number of specific advantages over the cross-sectional approach implemented in Section 4. Primarily, these advantages relate to the effects of unobserved heterogeneity within the sample. These effects are a function of the intangible or non-quantifiable influences on individual economic performance and include factors such as personal motivation, ability and work aptitudes. The panel data approach used in this section employs a random effects model to control for unobserved individual-specific effects[8].

Three main findings become apparent on the implementation of this random effects model:

- The statistical significance of the ρ term at the 1% level indicates that unobserved heterogeneity is a major influence on the probability of unemployment.
- Family characteristics also emerge as a strong, systematic determinant of labour market success. Specifically, these effects relate to the impact of family structure and parental education levels.
- Even after the effects of personal characteristics, family background and unobserved heterogeneity are controlled for, youth from the lowest 20% of neighbourhoods by income are shown to experience a higher probability of unemployment. However, the concentration of vocational qualifications that affected labour market outcomes in the cross-sectional model is not a statistically significant factor in the model as it is currently specified.

It must be noted that the high level of aggregation that is implicit in defining neighbourhoods on the basis of postcodes has the potential to influence the strength of the neighbourhood effects observed in these models. There is more scope for unobserved heterogeneity to affect statistical results at higher levels of neighbourhood aggregation. This is because higher levels of aggregation are concomitant with greater degrees of diversity or heterogeneity in social structure.

The role played by the level of neighbourhood aggregation is evident in the outcomes of studies that have used more disaggregated or localised measures of neighbourhood structure. For example, Case and Katz (1991) used residence by housing block level as its neighbourhood variable while Overman (2000) used census collection districts for his

8 In this context, the use of random effects models represents a method of controlling for bias from unobserved variables that may impact upon an individual's likelihood of experiencing unemployment.

study. These "small area neighbourhoods" have tended to exhibit more acute neighbourhood effects than those found in postcode-level studies.

Data

The data used here is the largest and equal longest longitudinal sample that can be drawn from the AYS. It covers the years 1989 to 1994, for ages 17 to 22. Initially, 1,523 individuals were in this panel, and after sample attrition across the period this number reduces to 920 individuals.

As with the cross-sectional samples, a range of variables covering individual characteristics, education and family background are included. These variables are predominantly fixed for this period. Education variables and variables related to living arrangements represent the only dynamic variables in the model. While the majority of variables are the same as in the previous models, there a few minor differences. All education variables refer to the current highest level of educational attainment and thus they are dynamic variables. Due to small cell size problems with the no parents variable in preliminary estimation, the no parent and single parent variables have been combined. Neighbourhood variables are still fixed as at time of first interview[9].

The dependent variable in the panel models varies slightly from those in the cross-sectional modelling. This is due to differences in how full-time study is treated. Unlike in the cross-sections, individuals undertaking full-time study cannot just be excluded from the sample. Hence the alternative to being unemployed in the models here, is either being in employment or in full-time study.

Econometric Methodology

It is expected *a priori* that unobserved heterogeneity of individuals will impact upon the probability of experiencing an unemployment spell. While a reasonable number of controls for personal characteristics are included, they cannot fully capture differences in individuals' motivation, intangible work skills, personality and other unobservable factors. Hence, a strategy is required that controls for systematic individual-specific effects that comprise the effects of unobserved heterogeneity. As a large number of our variables are fixed across the sample period, a random effects model is the option preferred here for controlling for individuals' unobserved heterogeneity.

9 Alternatively, dynamic neighbourhood variables could be used. However, these would be likely to pick up local labour market conditions and spatial mismatch rather than neighbourhood effects.

A model of the probability of experiencing an unemployment spell is given by:

$$Y_{it}^{*} = \alpha + \beta_1 X_i + \beta_2 F_i + \beta_3 N_{ij} + \mu_{it}, i = 1,..., n; j = 1,..., m, t = 1,..., p \qquad (5.1)$$

Where the error term consists of two components:

$$\mu_{it} = \varepsilon_{it} + \sigma_t$$

where:

ε_{it} is a standard stochastic error term
σ_i is a individual specific random effect; capturing unobserved heterogeneity that is specific to the individual *i*.

The underlying relationship takes the form:

$$y_{it}^{*} = \beta' x_i + u_{it} \qquad (5.2)$$

Once again the probability of individual *i* experiencing an unemployment spell (y*) is unobservable, instead we observe a dummy variable y_i, defined as:

$y_i = 1$ if $y_{it}^{*} > 0$

$y_i = 0$ otherwise.

This leads to the estimation of equation 5.1 by a random effects probit estimation technique (Maddala 1987).

The impact of neighbourhood income levels and skilled vocational qualification levels are evaluated in separate models. As it did not come up as significant in any of the cross-sectional models, neighbourhood degree is not investigated further here.

Table 5.1 Estimates from Random Effects Probit

	NH Income		NH Vocational	
	Probit	Random Effects	Probit	Random Effects
Intercept	-0.87* (0.08)	-0.91* (0.09)	-0.87* (0.08)	-0.92* (0.09)
Male	-0.02 (0.04)	-0.02 (0.04)	-0.02 (0.04)	-0.02 (0.04)
NESB	0.35** (0.14)	0.40* (0.15)	0.35** (0.14)	0.41* (0.15)
ATSI	0.35*** (0.18)	0.37** (0.17)	0.36** (0.18)	0.38** (0.17)
VIC	0.11** (0.05)	0.11*** (0.06)	0.10*** (0.05)	0.10*** (0.06)
QLD	0.09 (0.06)	0.09 (0.07)	0.09 (0.06)	0.09 (0.07)
SA	-0.01 (0.08)	0.03 (0.09)	0.02 (0.08)	0.04 (0.09)
WA	-0.01 (0.08)	0.02 (0.08)	-0.003 (0.08)	0.02 (0.08)
TAS	-0.08 (0.13)	-0.09 (0.15)	-0.06 (0.13)	-0.07 (0.14)
ACT	-0.35 (0.20)	-0.36 (0.22)	-0.40** (0.20)	-0.41*** (0.22)
NT	0.61 (0.50)	-0.63 (0.46)	-0.61 (0.50)	-0.67 (0.46)
Year 10	0.003 (0.01)	0.003 (0.07)	0.003 (0.01)	0.003 (0.07)
Year 12	0.18* (0.04)	0.17** (0.07)	0.18* (0.05)	0.18** (0.07)
Trade	-0.29* (0.11)	-0.30* (0.11)	-0.30* (0.11)	-0.31* (0.11)
Diploma	-0.14 (0.14)	-0.10 (0.14)	-0.14 (0.13)	-0.09 (0.13)
Degree	-0.59* (0.12)	-0.61* (0.14)	-0.60* (0.12)	-0.62* (0.14)
Non-Govt	-0.08***(0.05)	-0.09*** (0.05)	-0.10** (0.05)	-0.11** (0.05)
Single Parent/No Parent	0.21* (0.06)	0.23* (0.06)	0.20* (0.06)	0.22* (0.06)
Psecon	-0.20* (0.09)	-0.27* (0.07)	-0.20* (0.07)	-0.24* (0.07)
Ptrade	-0.27* (0.09)	-0.33* (0.09)	-0.27* (0.09)	-0.33* (0.09)
Pdeg	-0.07 (0.08)	-0.11 (0.08)	-0.09 (0.08)	-0.12 (0.08)
Parent Not Employed	0.08*** (0.04)	0.08*** (0.04)	0.08*** (0.04)	0.08*** (0.04)
NHINC20	0.08 (0.06)	0.09*** (0.05)		
NHINC80	-0.08 (0.05)	-0.09 (0.06)		
NHVOC20				-0.02 (0.05)
NHVOC80				-0.02 (0.06)
σ		0.14* (0.02)		0.14* (0.02)
p>X2	0.00	0.00	0.00	0.00
Log Likelihood	-2545	-2520	-2548	-2522

Standard errors are in parentheses.

, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.*

Results

Table 5.1 presents the results from the random effects panel model of unemployment. Results from a pooled probit without controls for unobserved heterogeneity is also provided for the purposes of comparison. The sign and significance of the estimates do not differ markedly between the straight probit and random effects models, with one main exception. In the random effects model, the estimate on NHINC20 is larger and more efficient, making it statistically significant at the 10 per cent level. The strong significance of the ρ term indicates that the unobserved heterogeneity of individuals has a substantial role in explaining their likelihood of being unemployed. Individuals from a non-English speaking background or who are an Aboriginal or Torres Strait Islander face a significantly higher chance of being unemployed.

Again the influence of family characteristics on the labour market outcomes of youth is illustrated. Being from a single parent, or no parent present, family increases your likelihood of experiencing an unemployment spell. Having at least one parent with secondary or tertiary education reduces unemployment probability, but only the coefficient on secondary education is significant. Individuals with a parent with trade qualifications are substantially less likely to have experienced an unemployment spell, most likely this represents access to informal job networks or family business effects.

The completion of trade or degree qualifications reduces unemployment likelihood substantially. Individuals who complete Year 12 alone (with no post-secondary qualifications) face an increased probability of experiencing unemployment spells. Youth who gained their schooling through non-government institutions are less likely to be unemployed.

Even after controlling for personal characteristics, family background and unobserved heterogeneity, youth from less affluent neighbourhoods are more likely to experience unemployment during early adult labour market experience. This means that individuals who grew up in poorer residential areas face ongoing difficulties in the labour market at least until the age of 22. However, the results here provide no support for the hypothesis that neighbourhood skilled vocational qualification levels affect the employment prospects of youth.

6

CONCLUSION

Findings

This study has sought to evaluate the impact of differential neighbourhood composition on the labour market outcomes of Australian youth. In particular, the focus has been on the relationship between concentrations of socio-economic disadvantage and advantage and the probability of being unemployed during early adult labour market experience. This focus on unemployment distinguishes our study from existing Australian research on neighbourhood effects which have concentrated on neighbourhood impacts on educational decisions / outcomes.

The principal finding is that neighbourhood composition does appear to affect the labour market outcomes of Australian youth. Specifically, our modelling has uncovered the following effects:

- The cross-sectional model indicates that significant neighbourhood effects on unemployment outcomes exist in high and low-income areas. While the positive effects of living in a high-income neighbourhood diminish by the age of 21, the negative effects associated with low-income neighbourhoods persist.

- The neighbourhood concentration of vocational qualifications is also a significant factor in the cross-sectional model. Specifically, it is found that low concentrations of such qualifications effect the unemployment outcomes of young people. This could be an indicator of the weaker employment and information networks that typically exist in low-income neighbourhoods.

- To examine neighbourhood effects more closely, a panel data model was constructed. This allowed the implementation of controls for the unobserved heterogeneity of individuals.

- The panel data model indicates that unobserved heterogeneity – that is, systematic individual-specific effects – is an important factor in the modelling of neighbourhood effects. This panel model confirms the presence of neighbourhood effects in the lowest 20% of neighbourhoods by income but does not corroborate the existence of effects related to the concentration of vocational qualifications.

Policy Conclusions

This study has provided evidence that neighbourhood composition influences the incidence of youth unemployment. Moreover, the quality of the neighbourhood that an individual resides in their teens continues to influence their employability until at least the age of 21. This indicates that spatial inequality has lasting effects on the labour market. As a result, continued urban and regional disparity may lead to sub-optimal economic outcomes, and the inter-generational transfer of social and economic disadvantage.

Evidence of neighbourhood effects has to be viewed in light of the continued difficulties faced by youth in the labour market. Employment opportunities for youth, especially full-time, have declined over the past two decades (Marks and Fleming 1998, Wooden 1998). Moreover, amongst youth, there are individuals who face particular difficult gaining employment. For instance, youth that do not complete high school are more likely to be unemployed, and experience longer unemployment duration (Miller and Volker 1987, Lamb 1997). Also, some sub-groups (such as Indigenous persons and those from non-English speaking backgrounds) within the overall youth labour market experience problems in the form of racial and/or linguistic difficulties (Miller and Neo, 1997; Altman and Hunter, 1999). Introducing an emphasis on the role of neighbourhoods indicates that spillovers may occur from spatial concentrations of particular personal or family characteristics. In the context of the youth labour market, this means that an individual's social background may condition their employability. Furthermore, due to the operation of sorting and inter-urban migration, it is the inherently spatial nature of income and wealth inequality that gives rise to these spillover effects.

Traditionally, economic policy responses to unemployment have been based on promoting economic growth in the belief that the benefits will 'trickle down' to disadvantaged areas. However, Gregory and Hunter (1995) estimate that to return Australia to full employment, for every additional job created in the top five percent of neighbourhoods, approximately 12 jobs would need to be created in the lowest five percent of neighbourhoods. Moreover, there are large income multiplier differentials between low and high SES neighbourhoods. Hence, household expenditure in low SES neighbourhoods will have much smaller employment generating effects. As a result of this, macroeconomic responses to unemployment are unlikely to address issues of urban and regional inequality. Instead, measures to address both neighbourhood effects and spatial inequality must be linked to their source (Borland 1995). Practically, this means policies aimed at improving disadvantaged youths' role models, increasing information flows to disadvantaged neighbourhoods, improving the quality of disadvantaged neighbourhoods, and reducing the overall level of spatial inequality. Each is discussed in turn.

Neighbourhood composition is likely to impact on youth preference formation and decision making. In particular, youth perceptions of, and expectations from, education and labour market participation represent one of the most fundamental channels for the transmission of neighbourhood effects. Youth from low SES neighbourhoods may not have access to adult role models that have had positive experiences with education and employment. As a result, these youth may choose sub-optimal levels of educational attainment and labour market participation.

Similarly, a lack of contact with adults who are members of the core work force is likely to disadvantage youth in terms of their access to informal job networks. Evidence from the US indicates that informal job networks represent an important channel for gaining information regarding employment opportunities (Holzer 1987, 1988). For youth, because of their lack of work experience and their lack of access to internal labour markets, informal job networks will be especially important. Evidence from the AYS appears to support this view. Approximately 73 per cent of the jobs taken by individuals in the AYS were gained through what could be described as an informal job network[10].

Policies to alleviate problems stemming from peer / role model and information network asymmetries are difficult to formulate. To address peer / role model effects on youth decision making, policies need to be aimed at altering youth perceptions of the returns to education and employment. A number of methods of doing this have been suggested. Latham (1998) proposed the formulation of a disadvantaged schools policy aimed at breaking the undesirable social characteristic of low expectations. Under this approach schools are used to insulate youth from negative neighbourhood spillovers, and promote a culture of educational achievement and social participation. Through this the intergenerational transfer of unemployment may be avoided (Jensen and Seltzer 2000).

In the past, forced bussing has also been suggested as a method of overcoming negative links between socioeconomic disadvantage and poor educational performance. Bussing involves transporting some selected students out of poor neighbourhoods (and similarly transporting some out of more affluent neighbourhoods) to schools in less disadvantaged areas. This should have the effect of improving the ‘quality’ of peer groups for youth from poor quality neighbourhoods, and reducing their isolation from mainstream society. There are, however, a number of major problems with this policy. Those individuals bussed into schools in poorer areas will most likely fare worse. Furthermore, there is evidence to suggest that students who have a relatively lower academic ability may actually perform worse in situations where the average level of student ability is high (Davis 1966, Meyer 1970, Nelson 1972).

Where youth lack access to informal job networks as a result of the area they grew up in, intervention to improve job information in poor neighbourhoods may be warranted. Hughes (1991) proposed a policy initiative that aimed to link spatial concentrations of unemployed to job opportunities in other areas. The strategy involves the creation of job information systems in low SES neighbourhoods to improve the matching of workers to jobs; instituting labour market programs targeted at the unemployed in disadvantaged areas; and providing transports systems that facilitate inexpensive home to work transport. This strategy is designed primarily to improve cross-urban job matching and reduce the barriers to taking employment in other areas. Policies along these lines have two benefits, they increase the contact that youth in disadvantaged areas have with adults who are active parts of the labour market, and they may directly alleviate spatial differences in unemployment levels. However, these effects should not be overstated. If the neighbourhood remains an undesirable area to live in, those who gain employment may migrate out of the neighbourhood. In isolation, policies along these lines may merely increase the rate of ‘churning’ of employed individuals out of, and unemployed individuals into, these neighbourhoods. Hence, any information and job matching based policy must be combined with attempts to actively improve the quality of disadvantaged neighbourhoods and / or address overall levels of spatial inequality.

Enhancing the physical environment of disadvantaged neighbourhoods may be desirable. Importantly, this must be closely linked to the way that public housing is provided.

10 The largest areas were individual approached employer, information from friend or relative, offer from friend or relative and employer approached individual. However, a large proportion of jobs (15 per cent) were gained through responding to advertisements in the paper.

Existing public housing policies have been problematic in so far as they have exacerbated the tendency for disadvantaged individuals to group together spatially. By locating public housing in low cost, low socioeconomic areas successive Australian governments have promoted the movement of disadvantaged individuals into these areas. For instance, in the four censuses between 1976 and 1991 (inclusive) the bulk of public housing was located in the bottom two deciles of the distribution (Hunter 1995). Attempts have been made in some areas, for instance the northern suburbs of Adelaide, to increase the variety and improve the quality of public housing. In these areas, this was combined with incentives to private property owners to invest in their houses / property. This approach is intended to increase the socio-economic diversity of the area[11]. This may serve to reduce the agglomeration of disadvantaged individuals, and promote greater interaction between individuals in these areas and those of a higher socioeconomic standing.

As a final point, the emergence of disadvantaged neighbourhoods has clear links to the growth in income and wealth inequality. As a result, policy initiatives to reduce overall levels of inequality are likely to impact upon the spatial incidence of inequality. It is, however, beyond the scope of this report to examine this in further detail.

Further Research

Further research into the operation of neighbourhood effects in Australian youth labour markets is necessary to shed light on the specific microeconomic mechanisms that have generated the results found in this study. Technically, this study has considered neighbourhoods at a reasonably aggregated level (postcodes). However, the type of neighbourhood effects discussed in Section 2.2 operate at a lower level of aggregation. Therefore, a potential strategy for obtaining a finer picture of neighbourhood effects in Australia would be to use the census collection district component of the AYS to construct a panel data set. Analysis of this data set would also allow for more accurate estimates of neighbourhood effects and the inclusion of a more detailed set of variables. A method of controlling for full-time study episodes in the panel model could also be implemented. For instance all full-time study episodes could be omitted and an unbalanced panel data set constructed. Estimation using this model would then focus only on those periods when individuals where actively in the labour market.

Policy responses to address adverse neighbourhood effects can only be formulated if the channels / mechanisms through which spatial concentrations of disadvantage affect youth outcomes are identified. Hence, further research is necessary to isolate and identify the specific transmission channels of neighbourhood effects.

11 In the US, similar initiatives were made under the Community Partnership Strategy (CPS).

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Appendix 1: Variable Set

Dependant Variable

Unemployed	Binary variable, 1 indicates the individual was unemployed, in the cross-sectional model 0 indicates employed; in the panel data set 0 means employed or in full-time study.

Explanatory Variables

Male	Binary variable, 1 indicates male, 0 female.
ATSI	Binary variable, 1 indicates the individual is an Aborigine or Torres Strait Islander, 0 otherwise.
NESB	Binary variable, 1 indicates that first language spoken was not English, 0 otherwise.

Education

All refer to the highest level of educational attainment.

Less than Yr10	Binary variable, 1 indicated the individual has not attained year 10 qualifications.
Yr10	Binary variable, 1 indicated the individual has attained year 10 qualifications.
Yr12	Binary variable, 1 indicated the individual has attained year 12 qualifications;
Dip	Binary variable, 1 indicated the individual has completed a diploma;
Trade	Binary variable, 1 indicated the individual has completed a trade qualification;
Degree	Binary variable, 1 indicated the individual has completed a degree or higher.

For the cross-sectional models the omitted case is Year 12; For the panel models the omitted case is less than Year 10

Non-Govt	Binary variable, 1 indicates the individual attended a non-government high school, 0 if the individual attended a government school.

State

Vic	Binary variable, 1 indicates the individual was living in Victoria at the time of the interview, 0 otherwise.
Qld	Binary variable, 1 indicates the individual was living in Queensland at the time of the interview, 0 otherwise.
SA	Binary variable, 1 indicates the individual was living in South Australia at the time of the interview, 0 otherwise.
WA	Binary variable, 1 indicates the individual was living in Western Australia at the time of the interview, 0 otherwise.
Tas	Binary variable, 1 indicates the individual was living in Tasmania at the time of the interview, 0 otherwise.
ACT	Binary variable, 1 indicates the individual was living in Australian Capital Territory at the time of the interview, 0 otherwise.
NT	Binary variable, 1 indicates the individual was living in Northern Territory at the time of the interview, 0 otherwise.

Omitted Case is living in New South Wales.

Section of State

Country	Binary variable, 1 if individual was living in a country town or village at the age of 14, 0 otherwise.
Rural	Binary variable, 1if the individual was living in a rural area of age 14, 0 otherwise.
Other City	Binary variable, 1 if the individual was living in a city other than a capital at the age of 14, 0 otherwise.

The omitted category is living in a capital city at the age of 14.

Family Background Characteristics

Family Structure

Single Parent	Binary variable, 1 if the individual had only one parent present at age 14, 0 otherwise.
No parent	Binary variable, 1 if the individual had neither parent present at age 14, 0 otherwise

The omitted case is both parents present at age 14.

Parents' Education

Psecon	Binary variable, 1 if the individual had at least one parent who attended secondary school.

Ptrade	Binary variable, 1 if the individual had at least one parent with a trade qualification
Pdeg	Binary variable, 1 if the individual had at least one parent with a degree qualification

The omitted case is no parent with secondary or higher education.

Parent Not Employed	Binary variable, 1 if the individual had at a least one parent who was not employed.

Neighbourhood Characteristics

NHINC refers to the income level of the neighbourhood

NHINC20	Binary variable, 1 indicates the individual is from a neighbourhood in the bottom 20 per cent of the neighbourhood income distribution, 0 otherwise.
NHINC80	Binary variable, 1 indicates the individual is from a neighbourhood in the top 20 per cent of the neighbourhood income distribution, 0 otherwise.

The omitted case is individuals from the middle 60 percent of the neighbourhood income distribution

NHDEG refers to the proportion of adults in the neighbourhood with degree qualifications or higher.

NHDEG20	Binary variable, 1 indicates the individual is from a neighbourhood in the bottom 20 per cent of the neighbourhood degree distribution, 0 otherwise.
NHDEG80	Binary variable, 1 indicates the individual is from a neighbourhood in the top 20 per cent of the neighbourhood degree distribution, 0 otherwise.

The omitted case is individuals from the middle 60 percent of the neighbourhood degree distribution

NHVOC refers to the proportion of adults in the neighbourhood with skilled vocational qualifications.

NHVOC20	Binary variable, 1 indicates the individual is from a neighbourhood in the bottom 20 per cent of the neighbourhood skilled vocational distribution, 0 otherwise.
NHVOC80	Binary variable, 1 indicates the individual is from a neighbourhood in the top 20 per cent of the neighbourhood skilled vocational distribution, 0 otherwise.

The omitted case is individuals from the middle 60 percent of the neighbourhood skilled vocational distribution.